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FINANCIAL ECONOMICS OF THE SHADOW BANKING SECTOR IN THE PROVISION OF SAFE MONETARY ASSETS IN THE UK

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FINANCIAL ECONOMICS OF THE SHADOW BANKING SECTOR IN THE PROVISION OF SAFE MONETARY ASSETS IN THE UK

by

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A thesis submitted to the University of Plymouth
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Dedication

For Emily, Jono, Mum, and for Dad

Acknowledgements

Writing a PhD thesis can often feel like an immensely solitary endeavour. That said, this dedication is testament to the countless people who supported this work over the years with insightful comments, encouragement, humour, or simply good company.

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So thank you all, so very much - and to anyone I have failed to mention by name, in no way does that diminish the importance of your contribution, and I thank each and every one of you from the bottom of my heart.

Author's Declaration

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Doctoral College Quality Sub-Committee.

Work submitted for this research degree at the University of Plymouth has not formed part of any other degree either at the University of Plymouth or at another establishment.

A programme of advanced study was undertaken, which included taught modules.

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Abstract

We study the role of the so-called 'shadow banking' sector in innovating aggregate money supply and providing safe assets to meet demand from assetholders with a need for low-risk, high-liquidity monetary services. We consider the measurement and literature around shadow banking to date, econometrics of modelling money demand, and latent factor approaches. In doing so we contribute to a literature around shadow banking founded on the papers of Pozsar, Adrian, Shin, Gorton, Metrick, and their various co-authors. We set the shadow banking sector within the financial frictions paradigm espoused by Bernanke and co-authors, and our empirical approach builds on the work of Johansen & Juselius (1990), as extended by Stock & Watson (2002). The focus on demand for money in the UK follows the work of Drake & Chrystal (1994). The quarterly-frequency dataset collected follows the work of Errico et al (2014), and covers 38 variables from Q1 1984 to Q2 2016 (130 quarters). The empirical methodology extends the Factor-Augmented VECM approach of Banerjee & Marcellino (2009), and introduces a novel technique of time-cluster analysis in Principal Component space. A novel identification strategy is also applied, extending the work of Johansen & Juselius (1990). Assessing hypotheses due to Pozsar (2013) and to Krishnamurthy & Vissing-Jorgensen (2012), we find evidence that shadow-bank-created 'money' is treated as a safe-asset substitute both for government debt and for deposits in the regulated banking sector.

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List of Abbreviations

ABCP: Asset-Backed Commercial Paper
ABS: Asset-Backed Security
CDF: Cumulative Distribution Function
CDO: Collateralised Debt Obligation
CP: Commercial Paper
EAA: Euro Area Accounts
ECB: European Central Bank
FI: Financial Intermediary
FFoF: Federal Reserve Flow of Funds
GSE: Government Sponsored Enterprise
HF: Hedge Fund
ICPFs: Insurance Corporations and Pension Funds
LPFC: Limited-Purpose Finance Company
MFIs: Monetary Financial Institutions
MMDA: Money-Market Deposit Account
MMMF: Money-Market Mutual Fund
MMI: Money-Market Instrument
MTN: Medium-Term Note
OFIs: Other Financial Intermediaries
Repo: Sale-and-Repurchase
SBS: Shadow Banking System
SIV: Structured Investment Vehicle
SPV: Special Purpose Vehicle
TBS: Traditional Banking System
TRS: Total Return Swap

Chapter 1

Introduction

"Money markets are frequently a backwater, except when they are not, in which case they are cascading rapids... [in August 2008] global money markets became not just cascading rapids, but roaring waterfalls. The financial world will never be the same after the US Treasury and Federal Reserve's fateful decision on the weekend of September 13-14 to stand aside, as Lehman Brothers plummeted to death on the rocks below"

Paul McCulley, 2009

1.1 Outline of Thesis

National economies have endured financial crises before. The South Sea Bubble of 1720 prompted the Bank of England to become one of the world's first Central Banks. The free banking era in the United States (1837-1862) led to the failure of around 50% of the state-chartered banks active during this period, and engendered the creation of the Federal Reserve System – arguably the most prominent Central Bank in the world today. However, the 'Great Recession' of 2008, preceded (and perhaps in no small part caused by) a bank lending pullback known at the time as the 'Credit Crunch', was notable for its global reach and profound and long-lasting consequences in the form of low growth, wage stagnation, historically low interest rates and damaging fiscal austerity in the United Kingdom.

The credit crunch was in turn preceded and likely precipitated by a valuation crisis in the US 'subprime' mortgage market – high-risk, high-yielding loans to low-income borrowers with poor credit ratings. These loans were frequently 'securitized' – the firm advancing the money to the ultimate borrower was in turn advanced that money by a firm with cash on hand that could not or would not merely be left in a conventional bank deposit account. In exchange, the finance firm in contact with the client sold the right to the borrower's stream of repayments to the upstream firm, appropriately discounted and promising an interest rate indicative of the risk associated with the transaction – yet often, for reasons that will be explored in due course, with a rating-agency assessment that the product was far less risky than its ultimate borrower's credit characteristics might suggest. This essential process was iterated into the many acronyms familiar to a news-watcher of September 2008 – CDOs, CMOs, CDOs-squared, Synthetic CMOs. These financial securities, and many others, along with the chains of financial market participants that they connect, constitute what Paul McCulley termed the 'Shadow Banking System'(SBS) – a capital-markets based analogue of the deposit-taking and loan-making activity of the traditional bank as popularly envisaged.

10 years have passed since the subprime crisis, and the shadow banking system is an active area of economic research – though substantial research questions of interest exist, particularly with respect to the shadow banking system outside the US. There remain differing estimates of the scale of shadow banking activity – including anywhere from 50% to 150% the size of the regulated banking sector [Pozsar et al., 2010]. The simple question of economic good or bad remains to be further studied. Does the shadow banking system extend credit to those 'underbanked' whom the regulated sector is unwilling or unable to serve? [Purnanandam, 2010]. Access to credit is generally held to be conducive to economic growth. Does the SBS compete with the TBS (Traditional Banking Sector) in loan markets, aiding credit price discovery and market efficiency? On the other side of the balance sheet, does the shadow banking sector have a beneficial role in producing safe assets to meet otherwise unmet demand? What is the role of the SBS in responding to central bank monetary policy? What is its role in

money creation- should its deposits be considered money or near-money, or are they better modelled as equity-like liabilities? The latter suggests a role for an analysis of the SBS in assessing the narrow-banking proposals of, for example, [Cochrane, 2014] and the 'Chicago Plan Revisited' of [Beneš and Kumhof, 2012] - all-equity funded lending having some similarities with the process of securitisation. Does the mark-to-market nature of credit extended by the SBS help investors accurately gauge credit risk, or does the securitisation process obscure information to broaden the extension of credit by mitigating information asymmetries that could lead to market failure [Dang et al., 2017] - and is to do so welfare optimal?

Various authors have considered shadow banking from the perspective of safe asset demand or as a response to financial frictions. Pozsar and co-authors have produced a series of highly detailed descriptive papers concerning the 'plumbing' of the US shadow bankings system [Pozsar et al., 2010, Pozsar, 2013, Pozsar, 2014]. Gorton & Metrick concern themselves with the functioning of repo markets in meeting demand for safe assets [Gorton and Metrick, 2009, Gorton et al., 2012, Gorton and Metrick, 2012]. Krisnamurthy & Vissing-Jorgensen offer a quantitative approach to assessing the substitutability between government debt and other safe financial assets for both the US [Krishnamurthy and Vissing-Jorgensen, 2012] and European case [Krishnamurthy et al., 2017]. Duca [Duca et al., 2014] considers drivers of activity in US shadow banking more broadly. However, no author of which we are aware has advanced the study of UK shadow banking beyond attempting to decribe and measure - the present study seeks to assess the UK shadow banking sector in the context of the well-established economic literature on money demand.

This literature divides demand for money into transactional, speculative, and precautionary motives [Fisher, 1911, Keynes, 1930, Hicks, 1989]. Each of these motives may be hypothesised as having a different demand function, and a different relationship with the opportunity cost of holding money. Shadow-bank-issued safe assets are best considered as meeting (changes in) the speculative demand for money - Keynes's liquidity preference, though the work of Gorton *et al* [Gorton et al., 2012] in highlighting the consistency of the safe-asset share in the US economy suggests an important role for the transactional and precautionary motives also. The broader literature on money demand typically concerns demand for real money balances, and emphasises the speculative motive which relates demand for real money balances to their opportunity cost - that is the interest rate available by exchanging that money for other financial assets. The precautionary and transactional motives may be hypothesised as being less price-elastic in nature, and so it is the speculative (i.e. the risk-vs-reward) motive which is being studied when relating demand for money to non-money interest rates available. Sriram however [Sriram, 1999] notes that the different theories giving rise to demand for money nevertheless have variables in common, and as such a consensus in the literature is that empirical work on money demand is not atheoretic, but is rather motivated by a blend of theories. Various authors including Drake & Chrystal, Hendry & Ericsson, and Nielsen [Drake and Chrystal, 1994, Hendry and Ericsson, 1991, Nielsen et al., 2004] have considered the case of money demand in the United Kingdom – but to the best of our knowledge, none have set the shadow banking sector within this framework.

This study proposes to define and describe the shadow banking sector within the UK, and set the sector's activity in the context of speculative demand for real money balances. To do so, a large dataset was constructed from time-series financial and real-economy variables as reported by the Bank of England, the Office for National Statistics, and the International Monetary Fund. The dataset comprises (up to) 898 variables at the Monthly or Quarterly frequency, back as far as 1969:Q1 in some cases, though this is not typical. The dataset has a great many missing observations, but is acceptably dense after 1987:Q1. In aggregate, we have access to 59,299 quarterly variable:timeperiod datapoint pairs, and 95,131 monthly datapoints. The research questions of interest are:

- What is the extent of shadow banking sector activity in the UK?
- Does shadow banking sector activity in the UK play a role in the provision of safe monetary assets?
- Are these pseudo-monetary assets treated as a substitute for govern-

ment debt or deposits in regulated banks?

These are developed into specific hypotheses in chapter 3. To address these broad questions, we subsequently follow the work of Errico *et al* [Errico et al., 2014], who map and assess the extent of shadow banking activity in the US using the Federal Reserve's Flow of Funds dataset to reconstruct the balance sheets of financial sector participants from central government to households – we attempt to approximate their analysis using UK data from the ONS United Kingdom Economic Accounts aggregate balance sheet dataset, also in chapter 3. Thereafter, we retrieve time-series of the relevant variables from this analysis, and combine them with other financial sector and real-economy variables. Following the work of Stock & Watson [Stock and Watson, 1999, Stock and Watson, 2002, Stock and Watson, 2005], Jurado *et al* [Jurado et al., 2015] and Bernanke *et al* [Bernanke et al., 2005] concerning Factor-Augmented Vector Autoregressions (FAVAR) and the dimensionality-reduction strategy Principal Components Analysis (PCA), we seek to aggregate the various and disparate measures of (and proxies for) shadow banking activity into a single synthetic time-series variable incorporating as much information as can feasibly be extracted from the dataset. Combining this synthetic variable with other time-series from the large dataset, we construct a suite of vector error-correction models to assess the extent to which shadow banking activity affects, and is affected by, macroeconomic conditions in the United Kingdom.

Though we find some support for our hypotheses and some functional forms with desirable econometric properties, the evidence is far from conclusive. We extend the study further into exploratory factor space, and introduce a time-clustering approach to analyzing time-varying relationships – which is believed to be novel in this field.

Addressing these questions is as vital as ever, though now in 2019 the scarcity of government-guaranteed paper that prompted initial innovation in composition of the money supply has reversed. With government debt plentiful but yields close to or below 0% across much of Europe and the developed world, central banks stand as the major buyers of sovereign paper, while private-sector money managers 'reach for yield' and corporate cash pools build up (and continue to demand safety) as firms hold back from investing in risky products despite abundant cheap capital. An understanding of how this demand for safety interacts with policy interest rates and the conduct of monetary policy will be vital for central bankers seeking to fight the next downturn with limited room for cutting rates before having to have recourse to extraordinary policy. Our work suggests that it is very likely that private-sector demand for above-all safe warehousing for capital is highly inelastic, and even extraordinary monetary policy has little ability to 'force' investors to take risk and stimulate the real economy. Explicit nominal GDP targeting and extraordinary fiscal policy such as 'helicopter drops' of money directly to consumers have been suggested as initiatives to counteract what is once more being called 'secular stagnation' [Summers, 2014]. If we indeed now inhabit a world where non-risk-taking capital cannot earn a positive nominal return, distinguishing demand for safety from demand for yield will be vital in assessing potential for future economic growth.

The structure of the thesis is as follows. Chapter 1 introduces the key theoretical literature in financial economics and economics of banking, Chapter 2 assesses the state of shadow banking sector research. Chapter 3 draws on the preceding chapters to develop hypotheses for statistical study, and describes the Errico *et al* [Errico et al., 2014] balance sheet analytical procedure, introducing our results from applying this process to UK data. Chapter 4 replicates some established functional forms from the money demand literature, and applies these to single-variable measures of shadow banking activity. Chapter 5 introduces and enacts the method of principal components for latent factor analysis, and continues this work into exploratory factor and time-clustering approaches. Finally, Chapter 6 reflects on the research outcomes, limitations, and avenues for future work.

1.2 Perspectives on Money and Banking

1.2.1 Money

Economics in the popular imagination is the study of money, and in that same psyche banks are inseparable from the money they notionally house. A slightly more sophisticated view is memorably outlined by James Stewart's George Bailey in Frank Capra's 1946 film It's a Wonderful Life;

> *"You're thinking of this place all wrong, as if I had the money back in a safe – the money's not here, your money's in Joe's house, right next to yours! And in the Kennedy house, and Mrs Macklin's house and a hundred others."*

Though a passable description of financial intermediation, this explanation too is incomplete, not least in so far as Bailey Brothers' Building and Loan was a Regulation Q thrift, a mutually-held financial intermediary (FI) much closer to the shadow banking entities that are the subject of this work than to a high-street commercial bank. Banks provide credit, and in doing so create money (McLeay et al, 2014) – bank deposits represent the great majority of money in a modern economy, 97% of broad money in circulation as of November 2013. In so doing they both provide credit to positive-net-present-value projects that may not otherwise have taken place, and supply a product – bank deposits – that meets a demand. For much of the 20th Century however, conventional theoretical microeconomics abstracted away from the counting of coins and current account balances, focusing instead on the allocation of real resources in the form of numeraire generic consumption goods. That is not to say that money is entirely absent from a mainstream economic view of the world – merely that the role of money is as a facilitator of exchange and of quantifying resource wealth, leading ultimately to the same allocation as would have obtained with some other entity fulfilling these roles.

Jevons [Jevons, 1885] highlighted these two functions of money – a medium of exchange and a unit of account – in addition to two others, holding also that money functions as a standard of value, and as a store of value. The role of money as a standard of value is similar to its function as a measure, though relies more on universal acceptability for the settlement of debts. Indeed, no 19th Century economist long discusses money before mentioning debt, though standard practice at the time was to cast money not as a means of settling debts, but as a means of enabling transactions otherwise thought to have relied upon barter. In this paradigm money is seen as a means to avoid the need for a 'double coincidence of wants' – the happenstance that, having some surplus with which to barter, an economic agent encounters a trading partner who has what she needs and needs what she has. The notion of money as a successor to a barter economy occurs in introductory textbooks such as Sloman & Wride [Sloman and Wride, 2009], and has a precedent stretching to the foundational text of the field of political economy, Smith's *On the Nature and Causes of the Wealth of Nations* [Smith, 1776].

However, Graeber [Graeber, 2012] notes that these are pure thought experiments, and very seldom is any evidence for a barter period preceding a monetary economy present in the historical, anthropological or archaeological record. Rather, barter is most readily documented between economic actors used to transacting with money but for some reason deprived of it – perhaps during a financial crisis, or in the canonical example, the use of cigarettes as currency in prisons or PoW camps. In this latter example it will be readily seen that it is the fulfilment of the four functions of money that adds value, rather than any characteristic of money itself- the functions then precede the entity, and there is no reason why all four needs must be met by a single entity. In fact the differing functions imply differing ideal characteristics of the entities that perform those functions – a store of value or medium of exchange might be light, portable and non-perishable, easy to store and retrieve, while a unit of account need have no physical form at all. Indeed in our modern economy bank deposits function as a store of value and as a medium of exchange, employ the pound sterling or the dollar as a unit of account, but take on physical form only when exchanged for banknotes or coins.

Prior to the establishment of banks or even the development of precious metal specie, Graeber [Graeber, 2012] argues that it was credit and debt - not barter - that gave rise to the need for the four functions of money to be met. A sufficiently small community might solve the double coincidence of wants problem by allowing the two transfers that constitute a barter exchange to take place at different times – creating an IOU stored in a kind of communal memory. Smith saw in human nature "a certain propensity ... to truck, barter, and exchange one thing for another" [Smith, 1776] but even more fundamental might be the human affinity for reciprocity [Bendor, 1987] – to do for one another favours, and keep a mental ledger of favours owing and owed. From this attribute, as societies grew larger and more complex, arose the need to record these arrangements in a consistent unit of account, with an agreed standard of value, to be settled in an acceptable medium of exchange [Graeber, 2012], and thus the need for money.

Throughout history money has variously been created by private enterprises and by state governments, often based on precious metals. Since the dissolution in 1971 of the Bretton Woods system, state-created fiat money has been considered typical in developed economies. States require taxes to be settled in their fiat currency, ensuring its use as a unit of account and widespread acceptability as a medium of exchange. Further, fiat currency states are not constrained by a fixed supply of precious metal in the amount of currency they can issue – freeing central banks to target other economic outcomes of importance, such as price level control. In practice, such economies rarely wish or attempt to control the quantity of money supplied, preferring to adjust the price of money in the form of interest rates. State money constitutes an asset of the holders without necessarily being a liability of the state – though one might think of the asset side of the state's balance sheet as being future tax revenues, or just a kind of national net wealth.

The question of whether such money constitutes net wealth or is offset by future tax liabilities begins with Ricardo [Ricardo, 1820] and depends on model assumptions about wealth transfer between generations [Weil, 1991] as well as the specific tax structures in question. In the recent paradigms of Modern Monetary Theory and Post-Keynesianism, as well as the work of Keynes himself, government spending is the prior act – the state spends money into existence. In doing so, the government issues debt, which in Ricardian equivalence implies a future tax to repay – even if such tax is indefinitely far in the future – and the corresponding need for economic actors to save in order to pay this tax prevents any aggregate demand impact.

In Modern Monetary Theory (MMT), the state is not constrained by the need to fund borrowing with future tax revenues – the central bank stands ready as a willing purchaser of government debt and can create reserves to do so. MMT focuses upon central bank reserves as the ultimate form of money, and reserve control as the key aspect of central banking – in this paradigm it would be undesirable for government to be debt-free, as government debt issuance allows injection of reserves into the commercial banking system [Caverzasi and Godin, 2014].

In the shadow banking system government bonds in fact perform many of the functions of base money for nonbank financial intermediaries who cannot access central bank reserves directly – they constitute a store of value and a medium of exchange in sale-and-repurchase (repo) secured lending transactions. The reuse by rehypothecation of the fixed quantity of government debt allows the shadow banking system to meet some of the demand for safe assets in the economy [Gorton and Metrick, 2012, Krishnamurthy and Vissing-Jorgensen, 2012].

1.2.2 How banks create money

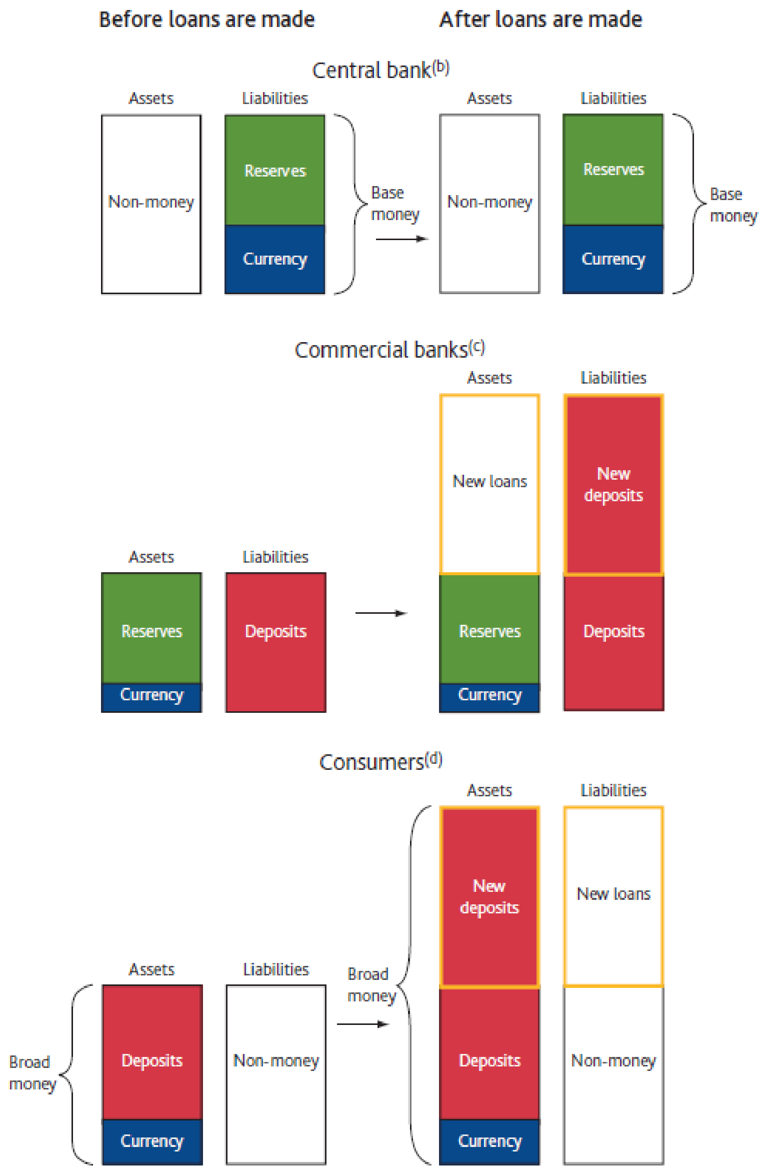
McLeay, Radia and Thomas [McLeay et al., 2014] artfully set out the monetary role of commercial banks in the first publicly available Bank of England research paper embraces the view that commercial banks create money when they lend – and so depart from the view that commercial bank lending is constrained by a central bank reserves multiplier. While a level of reserves was legally required in the UK before 1981 and was voluntarily set until 2009 – and remains a requirement in the US – this constraint does not bind, provided central bank reserves are readily available to commercial banks demanding them. The constraint on bank lending is rather profitability of lending projects, and so commercial banks may be expected to lend without limit to borrowers for whom the expected rate of return is believed to justify the risk. In making a decision to lend, the commercial bank unilaterally expands its balance sheet, matching its new loan asset with a corresponding deposit liability in the borrower's account with the bank – a deposit which of course is expected to be withdrawn or otherwise spent, deposited in the bank of the seller of whatever is purchased with the loan, and settled between the commercial banks by transfer of central bank reserves.

Correspondingly, commercial bank created money is destroyed when loans are repaid, and the whole process is conditional on easy access to functionally unlimited central bank reserves by the commercial banks – clearly this violates the Modern Monetary Theory predicate that reserve control determines the money supply. Instead the central bank seeks to influence commercial bank lending decisions by setting the interest rate price of reserves – for a given universe of investable projects, the lower the interest rate the larger the number of these projects have a positive expected rate of return and so will be approved for loans, expanding the money supply.

1.2.3 Microeconomics of banking

Banks however are not mere benevolent providers of the transaction medium. As with any profit-maximising firm in the economy, they produce products that are demanded, and consumers pay for those products. One of these is access to credit itself, and it is in this form that a financial sector enters the otherwise money-free general equilibrium paradigm of microeconomics attributed to Arrow, Debreu and McKenzie [Arrow and Debreu, 1954, McKenzie, 1959]. Specifically, access to credit allows agents to smooth consumption – to have a time path of consumption that is not constrained by a potentially uncertain time path of income. Given the risk aversion implied by preference convexity / diminishing marginal utility, the typical economic agent has that expected utility of a given wealth outcome is higher than utility of the same wealth in expectation but over disparate outcomes: access to financial contracts can help risk-averse consumers smooth consumption by forgoing consumption in good states (by saving or buying insurance contracts) in exchange for a guaranteed minimum level of consumption in bad

Figure 1.1: Money creation by the aggreate banking sector making additional loans



[McLeay et al., 2014]. The following notes provide further explanation and definition of the various terms used in this figure:

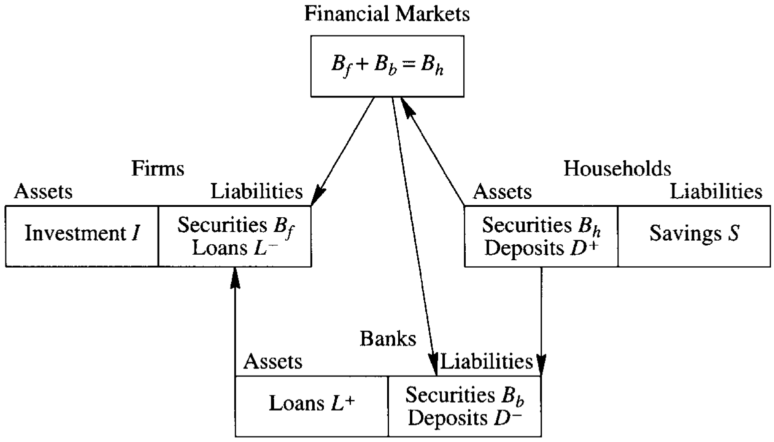
1. Balance sheets are highly stylised for ease of exposition: the quantities of each type of money shown do not correspond to the quantities actually held on each sectors balance sheet.

2. Central bank balance sheet only shows base money liabilities and the corresponding assets. In practice the central bank holds other non-money liabilities. Its non-monetary assets are mostly made up of government debt. Although that government debt is actually held by Bank of England Asset Purchase Facility, so does not appear directly on the balance sheet.

3. Commercial banks' balance sheets only show money assets and liabilities before any loans are made.

4. Consumers represent the private sector of households and companies. Balance sheet only shows broad money assets and corresponding liabilities – real assets such as the house being transacted are not shown. Consumers' non-money liabilities include existing secured & unsecured loans.

Figure 1.2: The Arrow-Debreu-McKenzie economy with redundant financial intermediaries



[Freixas and Rochet, 2008]

states.

In Arrow-Debreu however there is no requirement that financial intermediation be enacted by banks specifically- the following demonstration (figure 1.2) of this finding is reproduced from Freixas & Rochet's canonical 1997 treatise on the microeconomics of Financial Intermediaries (FIs) [Freixas and Rochet, 2008]:

We explain the model in more detail in order to motivate the financial frictions paradigm upon which much of the theoretical literature concerning shadow banking is based. As will be seen, absent such frictions not only is there no theoretical need for a shadow banking sector, there is little justification for the existence of any financial intermediary – including regulated banks. As figure 1.2 indicates, that this is a 3-sector, 2-period (t = 1, 2) model which omits the government and public sector for simplicity. The households (denoted subscript h) are endowed with 1 unit of the numeraire good, some to be consumed at t = 1, some to be invested by the firms (denoted subscript f) at t = 1 to produce consumption at t = 2. The rest of the model is presented in terms of a representative consumer, firm, and bank (subscript b), with holdings of investment, bonds, loans, deposits and savings denoted I, B, L, D and S respectively- thus for example B_h denotes the bonds held by households. Numerical subscripts denote time in the 2-period framework, thus for example (C_1, C_2) represents the division of consumption by households between period 1 and period 2.

The consumer

The consumer selects consumption profile (C_1, C_2) and the allocation of savings S between bank deposits D_h and bonds B_h to maximise her utility function given her budget constraints:

$$maxu(C_1, C_2) \tag{1.1}$$

$$C_1 + D_h + B_h = \omega_1 \tag{1.2}$$

$$pC_1 = \Pi_f + \Pi_b + (1 + r)B_h + (1 + r_D)D_h \tag{1.3}$$

where ω_1 represents initial endowment, p denotes the price of C_2 (second-period consumption), Π_f and Π_r are profits of the firm and bank respectively, and r and r_D denote the interest rate paid on bonds and bank deposits respectively. It will be noticed that in this model, bonds and bank deposits are perfect substitutes for the consumer, and so an interior solution will be found *iff* $r = r_D$.

The firm

The firm faces similar tradeoffs to the consumer, and seeks to maximise profit choosing an investment level I, and the funding mix between banks and capital markets given that the firm has no initial endowment:

$$max\Pi_f \tag{1.4}$$

$$\Pi_f = pf(I) - (1 + r)B_f - (1 + r_L)L_f \tag{1.5}$$

$$I = B_f + L_f \tag{1.6}$$

where f denotes the production function of the firm, and r_L the interest rate paid by the firm on its bank loans. L_f represents the aggregate quantity of loans extended to firms, and B_f the quantity of bond borrowing, and so equation 1.6 shows that the firm can only produce to the extent that it can borrow to invest, and sells its goods to the consumer at the price of second-period consumption p. Once more a corner solution will be adopted with either bank loans or capital market funding preferred unless $r = r_L$.

The bank

The final step then is to complete the model with the bank's loan supply and deposit demand, chosen to maximise profit:

$$max \Pi_b \tag{1.7}$$

$$\Pi_b = r_L L_b - r B_b - r_D D_b \tag{1.8}$$

$$L_b = D_b + B_b \tag{1.9}$$

That is to say that the bank's profit Π_b is its revenue from loans $r_L L_b$ less interest paid out on bond borrowing ($r B_b$) and interest paid on deposits ($r_D D_b$). The bank can only extend an aggregate volume of loans L_b to the extent that it can fund that credit with either deposits (D_b) or by borrowing in the capital markets (B_b). The equilibrium conditions are that each market should clear:

$$I = S$$

(Goods market)

$$D_h = D_b$$

(Deposit market)

$$L_f = L_b$$

(Loan market)

$$B_h = B_f + B_b$$

(Capital market)

and that each agent behaves optimally, i.e. solving 1.1-1.9 above. Based on the firm and household demand schedules above, we obtain that in equilibrium, $r = r_D = r_L$, banks make zero profit from 1.8 above, and firms and households are indifferent between bank instruments and capital markets securities for borrowing or saving respectively.

1.2.4 Extending the model

Freixas and Rochet extend this model to the case of uncertainty, obtaining that with perfect access to complete financial markets, and based on the no-arbitrage assumption, there will exist a complete continuum of state-dependent Arrow securities, each of which pays 1 numeraire in state $s(s \in \Omega)$ and zero otherwise, with corresponding prices p_s, and where Ω represents the set of all future states. Suppose a bank issues a security j characterised by the array $x_s^j(s \in \Omega)$ of its payoffs in all future states s. That is to say that x has j rows, one for each security, and s columns, one for each possible future state, and the typical element is the payoff of j in state x. For Arrow securities, paying 1 in state s and 0 otherwise, this will be an identity matrix. Be it a deposit or a loan, by absence of arbitrage its price must be

$$Z^j = \sum_{s \in \Omega} p_s x_s^j \tag{1.10}$$

which is to say that the price of j is its expected value. Given j may be interpreted as a deposit *with* the bank or a loan *to* the bank, it is apparent that banks will still make zero profit, and so the general equilibrium model with complete markets is ill-equipped for the theoretical study of financial intermediaries.

The Arrow-Debreu-McKenzie paradigm is however based on strident assumptions, various relaxations of which can grant theoretical foundation for a financial sector. These assumptions include complete markets, perfect competition, zero transaction costs and preference convexity. The post-1970s emergence of the asymmetric information paradigm, wherein different actors possess differing information about economic variables will attempt to use this for their own profit, is highlighted by Freixas & Rochet [Freixas and Rochet, 2008] as critical to the theoretical study of financial intermediation. Borrowing from the field of industrial organisation, they note that in the presence of transaction costs or other 'frictions' in the transmission technology, intermediaries who buy from producers and sell to consumers can exist profitably. Freixas and Rochet here define a financial intermediary as "an economic agent who specialises in the buying and selling (at the same time) financial claims" [Freixas and Rochet, 2008], while elsewhere they define a bank as "an institution whose current operations consist in granting loans and receiving deposits from the public" [Freixas and Rochet, 2008]. They proceed to offer two main justifications for the existence of FIs conditional on the relaxation of the 'complete markets' assumption of Arrow-Debreu-McKenzie: first, that financial markets are not in practice complete; and second, that banks offer diversified services to their customers, visible only in the form of financial transactions. These relaxations yield a variety of models, and their respective extensions. Such frictions are of interest to us as they allow for the existence of a financial intermediation sector, and differences in these frictions between regulated and shadow banking may have a role in influencing the scale of shadow banking activity.

1.2.5 Incomplete information

Freixas and Rochet [Freixas and Rochet, 2008], theorised that information asymmetries may be introduced in advance of the lending decision (yielding adverse selection type problems), contemporaneously (involving problems of moral hazard), or in determining payoffs (costly state verification). Inasmuch as these information asymmetries lead to financial frictions such as monitoring costs, state-verification costs, or risk indivisibilities, and provided those transaction costs are not proportional to transaction size, investors will obtain economies of scale by organising into coalitions to share these costs, or to spread risk more optimally. Bryant [Bryant, 1980] presents a model in which financial intermediaries (FIs) arise as an optimal response to an exogenously-given liquidity shock of unknown size; consumers discover in the second of three periods whether they will have to consume 'early' or 'late' and are unable to insure against this risk in advance even in the presence of financial markets, as no single agent can observe the total state of the economy.

Traded securities are not contingent on the incidence of these shocks, but only on the endogenous price of the bonds, which in turn depends on the return to investing in the first period. Thus, too many agents still prefer to invest and suboptimal allocations are reached when some are forced to liquidate early, returning less than the initial investment. Formation by consumers of a financial intermediary can attain the optimal allocation by offering deposit contracts that provide, in exchange for a deposit of one numeraire in the first period, a withdrawal of optimal consumption level in either the second or third period when they discover their own type, and the FI can meet its obligations by storing assets in equal proportion to the early withdrawers and investing the rest (though no individual knows her type ex ante, the distribution of early and late types in the population is common knowledge) [Bryant, 1980].

However a Bryant-style FI cannot coexist with an asset market, and the bank's ability to fulfil its contracts depends on no late type idiosyncratically withdrawing early- which there is no unilateral incentive to do, absent an asset market. If however a late consumer does not trust the bank, does not trust her fellow consumers or does not believe that they trust the bank, the situation can degenerate quickly into the equilibrium bank run of Diamond and Dybvig [Diamond and Dybvig, 1983]. In this widely-studied model, the optimal FI contract promises early withdrawers a larger payoff than they would receive in the free market equilibrium, prompting concerns from late types (who nevertheless receive a larger allocation by leaving their deposit with the bank, yielding a Nash equilibrium with no runs provided all late types believe that all other late types will do likewise). If however they believe that other late types will withdraw early, types being unobservable, they will have an incentive to do likewise. This decision can be predicated only on observing the line at the bank in the early withdrawal period, which in turn faces a sequential service constraint, so cannot selectively suspend convertibility of deposits. Sources of mistrust may be given exogenously, as in the 'sunspot' bank runs of Anderlini [Anderlini, 1989], or based on certain agents receiving a signal about the likelihood of a bank run, after Postlewaite and Vives [Postlewaite and Vives, 1987]. Further, in a repeated interaction setting, agents may have an incentive to withdraw early if superior returns are available elsewhere, as in the continuous-time generalisation of Diamond-Dybvig offered by von Thadden [von Thadden, 1998]. Jacklin, writing in Prescott and Wallace [Prescott and Wallace, 1987] critiques the Diamond-Dybvig model on the basis that households with direct access to the market would prefer to meet short-term liquidity shocks by trading their contingent claims with patient types, making both better off, and rendering the bank redundant once more - and the defence of Wallace [Wallace, 1988] rests on imperfect access to incomplete financial markets.

As is becoming clear, FIs that arise in response to frictions in financial markets do not typically result in complete markets, but may introduce frictions of their own. Acharya and Naqvi [Acharya and Naqvi, 2012], contributing to the burgeoning post-crisis literature on the role of banks in destabilising (rather than optimising) the financial system, show how agency problems in FIs can induce mispricing of risk. In an expanded variant of the now-familiar Bryant-Diamond-Dybvig model, it is shown that in conditions of macroeconomic uncertainty, consumers may prefer to reduce their informational disadvantage by storing assets in the form of bank deposits- the abundant liquidity with which the bank is thereby afforded leads to relaxation of lending standards, "fuelling credit booms and asset price bubbles and sowing seeds of the next crisis" [Acharya and Naqvi, 2012]. The model is further enriched by giving agents of the bank itself perverse incentive structures - when they are compensated based on loan origination, but protected from downside risk unless bank liquidity minima are breached, they have an incentive to overextend credit, particularly when a flight-to-quality induced by poor macroeconomic conditions grants the banks surplus liquidity and appears to make breach of reserve covenants less likely. This is exactly the moral hazard problem.

The adverse selection information-asymmetry problem introduced above as a motive for the formation of FIs may also not be completely solved by their introduction- Broecker [Broecker, 1990] finds that FIs competing in a Bertrand-competitive setting will always attempt to undercut one another to improve the credit quality of their own clientele at the expense of others - with the aggregate outcome that too much credit is extended to unworthy firms. In this model a firm will accept the lowest interest rate immediately, so the only consumers who appear at successive banks are those who have been rejected from the first bank, assuming banks are visited in order of increasing interest rate. Banks lack the ability to price-discriminate, and interest rates are common knowledge. Thus the probability of a bank choosing to remain inactive is increasing in the number of banks in the economy. It should be noted however that Broecker assumes an imperfect bank creditworthiness test, rather than the fixed cost for perfect information formulation that can be mitigated by coordination. Bertrand competition allows a firm to supply whatever quantity of a good- in this case, credit- it desires at a particular price, while Bertrand-Edgeworth competition introduces a supply constraint. An analogue for this condition in FIs may be conceptualised as a minimum capital requirement, and indeed Thakor [Thakor, 1996] shows that in equilibrium, "credit-risk-based capital requirements increase credit rationing and lower aggregate lending". In the Thakor model, banks share costs for both pre-loan screening and post-loan monitoring, and an increase in exogenously-given capital requirements (eg by a government or regulatory body) increases the probability that any given agent will be denied credit by the entire banking system, with those banks facing the highest cost of capital responding most vigorously. Kisin and Manela [Kisin and Manela, 2016] offer empirical support for this proposition, finding that banks would prefer to offer guarantees to Asset-Backed Commercial Paper (ABCP) conduits which receive a more favourable capital requirement treatment- they ascertain that a ten percentage point increase in capital requirements would cost banks on average $143 million each, and cause lending interest rates to increase by 3 basis points, and volumes to decrease by 1.5 percent.

Just as not all potential loan customers of a theoretical bank are honest about the profitability of their projects, neither are all depositors wise, alert and efficiency-maximising investors. The status of bank deposits in the modern economy as a form of money requires the bank to provide something more than the investment yield that depositors might seek from a mutual fund or bond investment – secrecy. In the model of Dang, Gorton, Holmstrom and Ordonez [Dang et al., 2017] the very efficiency with which banks produce information on their borrowers imperils the use of their deposits as money. The ideal money-substitute bank deposit would have a stable, predictable value and any information that might cause this value to fluctuate would optimally be suppressed – depositors care more about minimising the volatility in the value of their money, than reassuring themselves of the solidity of the bank assets backing it. The Dang *et al* [Dang et al., 2017] world allows for banks to exist alongside a capital market, and postulates an equilibrium whereby banks invest in assets that are low-risk or for which information discovery is either prohibitively difficult, or unnecessary. Other projects will attract capital market funding. Notably, Dang *et al* [Dang et al., 2017] suggest that debt is an optimal asset for backing money-like liabilities, as its face value is constant – unlike traded instruments such as equity, whose price reveals information.

1.2.6 Macroeconomics of banking

The Thakor [Thakor, 1996] model also notes that the response of the banking system to public sector monetary policy depends on the effect of monetary policy on the term structure of interest rates, introducing a further motive for a good theoretical understanding of the functioning of financial intermediaries - the role of the financial sector in the macroeconomy, and in the transmission of government economic policy. The first-recognised channel, the so-called 'traditional' interest rate channel, is the key channel in the operation of the Keynesian IS-LM model. Subsequent authors have added other asset price channels [Modigliani and Miller, 1958], lending channels [Bernanke and Gertler, 1995], and risk-taking channels [Rajan, 2006, Borio and Zhu, 2012]. We will now proceed to examine each of these channels in a little more detail – the discussion which follows is in the spirit of Mishkin [Mishkin, 1996].

The traditional interest rate channels

The traditional Keynesian IS-LM model is widely taught on undergraduate macroeconomics courses, and operates as follows. An expansion in the money supply lowers the price of money in the form of real interest rates. This lowered cost of capital causes a rise in investment spending by firms and households, leading to an increase in aggregate demand and output [Mishkin, 1996]. Because of the role of real, rather than nominal, interest rates, this is a monetary-veil channel. Furthermore, the decision-makers are real-economy firms and households, and the role of the financial sector is limited. Mishkin however adds that due to the operation of this channel on real interest rates, monetary policy can still be effective with nominal policy rates at a zero lower bound – provided the money supply can be expanded enough to bring down real interest rates. In this sense, the model provides an intellectual basis for quantitative easing. Bernanke & Gertler [Bernanke and Gertler, 1995] however find limited empirical evidence for the operation of this channel in the data – what Bernanke & Gertler refer to as 'the neoclassical cost-of-capital' variable does not appear to be a predominating factor in corporate or household investment decisions at the margin. Taylor [Taylor, 1995] however, writing in the same edition of the same journal as Bernanke & Gertler, argues for substantial empirical effects of interest rates upon consumer spending, and thus for the importance of the interest-rate channel in transmitting monetary policy.

Asset price channels

As the interest rate channel is believed to operate upon the real economy only to the extent that the cost of capital affects firm and household investment decisions, it may be thought of as affecting only the fixed-income asset class – bonds. However the prices of other assets, and their attendant wealth effects, may also be believed to influence consumption. Notable in this category are exchange rates and corporate equity [Mishkin, 1996]. An expansion of the money supply or cut in policy interest rates make deposits in domestic currency less appealing relative to foreign currency – this devaluation of the domestic currency reduces the price of domestic goods relative to foreign goods, increasing net exports (either by a fall in gross imports or an increase in gross exports, or both). Taylor [Taylor, 1993] argues for the importance of this channel.

Two subchannels comprise the equity price channel in Mishkin [Mishkin, 1996] – Tobin's q [Tobin, 1969] and the wealth effects of Modigliani [Modigliani, 1971]. Tobin's q is defined as the market value of a firm divided by the replacement cost of capital. When this q is high, firms can issue equity that is high in value relative to the plant and equipment thus funded. The significance of this channel then rests in how monetary policy might affect the valuation of corporate equity, and therefore q. A monetarist story according to Mishkin [Mishkin, 1996] holds that expansionary monetary policy leaves equity buyers with too high a portfolio 'weight' towards money, more than is desired for speculative and other motives – they may rebalance away from money by buying equities, increasing equity prices and therefore q. An alternative, Keynesian theory in Mishkin [Mishkin, 1996] is that expansionary monetary policy makes equities more attractive relative to bonds, leading to a similar portfolio rebalancing effect. It will be seen that both these effects operate upon portfolio allocation decisions, respectively of potential borrowers and of buyers of financial instruments. Such portfolio-rebalancing effects will be encountered later, once more from the point of view of borrower firms, and also from that of financial intermediaries.

Modigliani's [Modigliani, 1971] wealth effects have much in common with the Keynesian case outlined above, but without the link through Tobin's q to aggregate output. Given some holdings of equities, when equities increase in value holders see an increase in their wealth, and may decide to consume some of it depending upon their marginal propensity to consume. Equity as used here can be broadly defined [Mishkin, 1996] – housing and land wealth may be included, and as a major component of the wealth of most households, changes in the valuation of this wealth can be consequential for aggregate demand. Such valuation shufts may be linked to monetary policy through the effect of monetary policy upon real interest rates, and thus dividend-discount valuation models of the Gordon type [Gordon and Gordon, 1997].

It should be noted that none of the channels above are entirely mutually exclusive – operating side-by-side, they may lead to accelerator or multiplier effects. A particular case of accelerator effect was outlined by Bernanke & Gertler [Bernanke and Gertler, 1995] , and we discuss that and the broader class of credit channels hereafter.

Credit channels

The credit channels outlined in the literature following Bernanke & Gertler [Bernanke and Gertler, 1995] emphasise the real-economy effects of the financial frictions arising from theoretical models outlined above. They may be subdivided into the bank lending channel and the balance sheet channels.

The bank lending channel is premised upon the notions that banks have an advantage in situations of informational asymmetry in credit markets [Fama, 1985] , and that different types and sizes of firms have differing levels of reliance on bank funding [Kashyap et al., 1992]. Provided that (for some borrowers at least) bank loans are not perfectly substitutable with capital market borrowing, expansionary monetary policy will increase the loan supply to borrowers with no alternative, expanding output. Clearly this channel could be sterilized by more closely-substitutable funding sources for such firms, or in a world where the availability of reserves is not the binding constraint on bank lending to profitable projects. Mishkin [Mishkin, 1996] notes that the bank lending channel may be becoming less relevant given post-1980s regulatory shifts relaxing the reserve constraint, and broadening diversity of funding sources. Jiménez *et al,* [Jiménez et al., 2014] assembling a large dataset of twenty-three million bank loans, find that lower overnight interest rates do indeed induce banks to lend more and with lighter covenants to riskier firms. They further document a symmetry between smaller firms reliant on bank borrowing, and more thinly-capitalised banks reliant on commercial lending.

The balance sheet channel also depends upon informational asymmetries in the market for credit. In this case the uncertainty surrounds the quality of assets on the borrower firms' balance sheets, which can be pledged as collateral against bank or capital markets borrowing. The presence of such uncertainty may lead banks to lend at above-optimal interest rates or below-optimal volumes, respectively overpricing or constraining credit, and in any case lowering investment spending and output – this is the external finance premium [Mishkin, 1996]. Monetary policy through this channel then operates via its effect on either the size or the uncertainty surrounding the size of firms' balance sheets. As seen above, expansionary monetary policy may increase the valuation of firms' equity – expanding their balance sheet and easing collateral concerns. Expansionary monetary policy can also soothe lenders' concerns by bolstering cashflow, improving debt interest coverage ratios [Bernanke and Gertler, 1995]. A third balance-sheet channel suggested by Mishkin [Mishkin, 1996] concerns the effect of monetary policy on the general price level. As debt has a fixed nominal face value, a general increase in price level should increase the nominal value of a firm's assets, while the nominal value of debt remains constant. Thus the ratio of debt liabilities to the firm's total assets falls, strengthening the balance sheet and making the firm more creditworthy.

Gertler & Kiyotaki [Gertler and Kiyotaki, 2010] and Gertler & Karadi [Gertler and Karadi, 2011] consider the balance sheet channel as it applies to banks themselves, noting that an inability to attract funding liabilities (either in retail deposit or interbank markets) may drive a spread between deposit and loan interest rates or constrain the volume of loans extended, communicating a financial-sector shock to the real economy. De Groot [De Groot, 2014] studies financial sector balance sheets in a Dynamic Stochastic General Equilibrium (DSGE) framework, finding that banks deleverage when monetary policy shocks are prevelant – a reverse-multiplier to real economic activity, and another case of the financial accelerator of Bernanke & Gilchrist [Bernanke and Gertler, 1995]. In general, the financial accelerator offers a mechanism by which endogenous shocks in credit markets may propagate to the real economy and their effect size be enhanced by leverage, whether by impact on borrower or lender firms' balance sheets.

The balance sheets discussed above are those of firms, but each has a household analogue. Like small firms, households most probably cannot access capital markets funding, and depend upon banks to smooth consumption or for investment in e.g. housing assets. The cashflow and nominal-rigidity-of-debt channels also operate for households [Mishkin, 1996]. Relative yields available on different financial assets may also affect household portfolio allocation decisions as seen in the money-balances approach above, and we turn now to examine the general class of these portfolio-choice channels – the risk-taking channels of monetary policy.

Risk-taking channels

Borio & Zhu [Borio and Zhu, 2012] apply the practical techniques used in investment management to the monetary transmission mechanism. The importance of interest rates and yields in portfolio allocation decisions by asset managers, and the dependence of these upon monetary policy, gives monetary policy a central role in influencing allocation decisions – with real-economy consequences. Borio & Zhu highlight three ways in which monetary policy can affect risk appetite and therefore allocation decisons; valuations, hurdle rates, and central bank communication [Borio and Zhu, 2012].

The valuation channel is instinctively close to the balance sheet and wealth effects outlined above. Lower interest rates boost the valuations of cashflow-generating assets, as well as freeing up cashflow if debt interest rates are floating. This effect also occurs on the balance sheets of financial firms themselves – as interest rates fall, equity prices rise, volatility falls and position-size and risk constraints on a trading desk ease, allowing for larger bets to be placed. 'Mechanical' models of mathematical risk can hardwire this effect [Borio and Zhu, 2012] , and Gambacorta [Gambacorta, 2009] finds empirical evidence for its existence and significance, documenting that an extended period of low interes rates is associated with an increase in risk taking by banks (as measured by realised bank default frequency).

The second effect depends upon 'sticky' target returns or 'hurdle rates' – as interest rates fall, target rates of return may be maintained at higher levels due to contractual investment mandates, long-term investors such as pension funds, or just speed-of-adjustment to a new risk regime. Initially, falling interest rates make these sticky targets easier to hit, increasing risk tolerance – however in a prolonged low-interest-environment, as assets reprice these targets become harder to hit, and hurdle rates may be lowered or, if not, investment managers may be incentivised to take on more risk to meet targets. This is the "search for yield" of Rajan [Rajan, 2006] and of Gambacorta [Gambacorta, 2009].

The third set of effects outlined by Borio & Zhu [Borio and Zhu, 2012] concerns the central bank directly. By committing ahead-of-time to particular targets – or in a more extreme case, to support certain markets – the central bank can compress risk premia, attracting investment to (and increasing prices in) that market. Borio & Zhu refer to this as the 'insurance effect', market participants referred to the 'Greenspan Put' in the 1990s, and in any case this is in effect moral hazard willingly entered-into by the central bank, assuming part of the risk distribution from market participants without explicitly charging for it. Such free risk warehousing naturally affects the approach of investors to pricing the risk remnant.

Bianchi [Bianchi, 2014] assesses the risk-taking channels in a DSGE framework. Three operational channels are highlighted: lowering the nominal interest rate reduces the real rate due to nominal rigidities (as in the traditional interest rate channels discussed above); lowering the real interest rate increases the present value of cash flows from bank-held assets, allowing for greater borrowing against them (as in the balance sheet channels above); and knowledge on the part of market participants regarding the propensity of the central bank to cut rates in cases of future financial distress encourages greater risk taking in the present (as with the willing-moral-hazard discussed immediately above). The risk-taking channels may thus be considered the most general channels by which monetary policy operates through the financial sector.

Chapter 2 will revisit these channels as they apply to shadow banking specifically, but having discussed supply & demand for loans, we return to the other side of the financial intermediary's balance sheet, and a consideration of demand for money.

1.2.7 Empirical studies of money demand

Relocated from Chapter 2

The review by [Sriram, 1999] of landmark findings in the demand for money literature highlights three of the functions of money in the economy previously mentioned – as a means of exchange, as a store of value, and as a unit of account- and adds a fourth, as a source of deferred payment. Demand for money may therefore be conceived as demand for one or more of the services money provides. The traditional value theoretical approach due to Hicks [Hicks, 1989] casts money as simply another asset to be chosen at optimal level from amongst a range of assets with differing yields and associated risks, subject to a wealth constraint- in marked contrast to prior and contemporaneous work focusing on money as simply a transactional medium to be held in proportion to the desire to make transactions, such as that of Fisher [Fisher, 1911]. Demand for transactional money was also emphasised by Keynes in establishing the key hypothetical negative relationship between demand for money balances and interest rates – interest rates represent the opportunity cost of holding (non-interest-bearing) money balances, and the money demand function is thus negative in (non-money) interest rates [Sriram, 1999].

Keynes further recognised that demand for money stems from precautionary and speculative, as well as transactional motives. Whilst demand for transactional money in the Keynesian conception is a relatively constant proportion of wealth, the demand for money for speculative reasons – the liquidity preference – emphasises the store-of-value function of money. It is this function that relates speculative demand for money to the interest rate, now considered as the alternative yield available by investing in bonds- resulting once more in a negative relationship with respect to prevailing interest rates, but also a relationship with anticipated future interest rates, the source of the Keynesian 'liquidity trap'. When the interest rate is very low, it is expected to rise in the future and money is thus preferred now, to be exchanged for bonds when yields rise and bond prices fall. Keynes' work was extended by Baumol [Baumol, 1952] and by Tobin [Tobin, 1956] in an inventory-theoretic approach to demand for transactional money, whereby money is held as an alternative to almost-as-liquid but higher-yielding financial alternatives because the transaction costs of switching justify maintaining money inventory. The store-of-value motive was extended by Tobin [Tobin, 1958] who recognised that money may be preferred as an asset due to the higher certainty of its lower yield – if risk and reward are conceptualised naively as moving in lockstep (perfectly positively correlated) then all assets should have the same expected value, and only preference for risk can discriminate between them.

It is this preference for safety that will later be hypothesised as driving demand for shadow-bank money-like assets when supply of government or other safe assets is otherwise constrained. Such constraints may result from government debt issuance policy not taking the role of sovereign paper as a safe asset and as high-quality collateral sufficiently into account – potentially leading to suboptimal levels of government debt 'supply' at times of financial distress, as perhaps has been the case with the recent austerity policy in the UK. While arguably wrong and inadvisedly procyclical even from a real-economy point-of-view – the government abdicating its role as demander-of-last-resort – it may also emerge that a reduction in government debt issuance at a time of flight-to-safety necessitates an expansion of the shadow banking sector at a time when prudential policy would be seeking a reduction in shadow banking activity. It seems highly likely that reduction in government borrowing, and therefore safe-asset issuance, during the pre-GFC years led to an expansion of the shadow banking sector – we will attempt to show that the sector arose in part to meet an unmet demand for safe assets.

The supply of safe assets may also be constrained, from the point of view of safe-asset buyers, by regulatory requirements such as deposit insurance upper limits. Pozsar [Pozsar, 2013] and co-authors [Pozsar et al., 2010] attribute a key quantum of demand for safe asset to corporate 'cash pools'. Managers of these cash pools, held to meet the transactional as well as speculative demands for money, prefer to avoid large, concentrated, unsecured exposures to specific banks – even if those deposits are insured [Pozsar, 2013]. Pozsar [Pozsar, 2013] views the next-best safe asset as short-term government bills but documents that the supply of these is insufficient to meet demand, measured as size of cash pools on US corporate balance sheets. In the presence of unment demand and willingness to pay for safety in the form of accepting lower yields, it is hypothesised that a key role of the shadow banking sector is to meet this demand. Before turning to a more detailed examination of the shadow banking system, we look now to antecedent empirical studies in the area of money demand.

A broad, deep and well-established literature in econometrics is concerned with estimating the form and parameters of the money demand function. Sriram [Sriram, 1999] notes that the different theories of demand for money nevertheless imply a relationship between observed quantity of money supplied and a set of observable variables linked to the real economy – including a scale variable such as GDP growth, and an opportunity cost of holding money such as the interest rate on alternative assets. Thus, all empirical studies of money demand may be conceptualised as assessing the blended demand for money, or the total demand for money arising from all motives – though different authors may emphasise different theories, and the different motives may be relevant in assessing short-term dynamics. The empirical study of money demand has also advanced the entire field of econometrics – indeed, perhaps two of the most important and influential papers in the field of analysing cointegrated time series – Engle & Granger's Co-Integration and Error Correction: Representation, Estimation, and Testing [Engle and Granger, 1987] and Johansen & Juselius's Maximum Likelihood Estimation and Inference on Cointegration with Applications to the Demand for Money [Johansen and Juselius, 1990] – both concern themselves with estimating money demand to demonstrate their novel methodologies. Sriram [Sriram, 1999], in a comprehensive review of the money-demand literature, motivates his study by noting that demand for money and the behaviour of monetary aggregates play an important role in guiding monetary policy actions – still perhaps true, albeit de-emphasised since most developed economies began to abandon monetary aggregates as a specific policy target in the late 1980s, the UK abandoning monetary aggregates in 1986 and switching to explicit inflation targeting in 1992. Nevertheless, monetary aggregates have remained a focus of study – and are now perhaps freer of the Lucas critique that policy targets make poor structural variables.

Systems of equations, estimated in vectorised forms, have characterised studies of money demand since their rise to prominence in the 1980s – often being demonstrated for the first time on models of money demand. Such formalisations allow endogeneity to be modelled rather than having to be controlled out. The vector error correction model, wherein a system of nonstationary variables share one or more stationary linear combinations, is commonly applied to the problem of estimating money demand and is easily extended to more complex, nonlinear, threshold, or parameter-switching functional forms.

Notwithstanding the econometric complexity that may be brought to bear on the problem, the essence of most money demand models is simple. Though empirical work may be motivated by any or all of the different theories of money demand, and studies may variously emphasise or de-emphasise demand for money resulting from transactional, speculative, precautionary or utility motives, as mentioned by Sriram [Sriram, 1999] they typically share a framework that connects the quantity of money demanded to a measure or measures of activity in the real economy, and to the opportunity cost of holding that money. Price homogeneity was established and empirically supported early on in the literature [Johansen and Juselius, 1990], and as such subsequent authors have typically modelled demand for real, rather than nominal money balances. Real GDP is often chosen as the measure of real economy activity, and the measures of activity and real money balances typically enter models in logarithms [Sriram, 1999]. The opportunity cost of holding money must be considered with respect both to that money's own rate of return and to rates of return available on competing assets, either domestically or abroad for the case of an open economy. These rates of return, being in percentage form, may enter models in logarithms or in levels. The parameters of a log-log model then estimate the elasticity of money demand with respect to the explanatory variable directly, while log-linear parameters may be interpreted as a semi-elasticity. Given the interest of the present study in establishing the elasticity of demand for shadow-bank money with respect to alternatives, logarithmic forms will typically be used.

Sriram's [Sriram, 1999] meta-analysis shows that a value of around 1 is typical for the coefficient of real money balances to real income – that is to say that demand for money grows 1:1 with real economic activity. However, studies report coefficients of below and above 1, and studies including multiple monetary aggregates typically find different scaling parameters for narrower or broader definitions of money – though the directionality is ambiguous. McNown & Wallace [McNown and Wallace, 1992], assessing the US case, find that the scale elasticity is higher (1.13) for broader (M2) money and lower (0.99) for narrower (M1) money, while Drake & Chrystal [Drake and Chrystal, 1994], considering corporate sectoral demand for money find the opposite – that the elasticity is highest for Divisia M1 at 3.3, and lowest for Divisia M3 at 2.6 [Sriram, 1999]. All authors in the Sriram metastudy find the expected positive semi-elasticity to money's own rate of return, albeit with magnitudes varying from +0.5 to +18.1 within a single study – Adam's [Adam, 1992] work on money demand in Kenya. Typical orders of magnitude are around +2.0 to +6.0. Most authors also document a negative semi-elasticity to alternative interest rates, depicting the expected opportunity cost phenomenon –indicative semi-elasticities here vary from -0.008 to -10.1 depending upon the alternative investment return offered.

Turning to the case of antecedent studies concerned with the United Kingdom, Drake & Chrystal [Drake and Chrystal, 1994] examine specifically corporate demand, and measure money using the Divisia aggregates. Reasoning that corporates and households have different motives to demand money, they consider money an input into the utility function of industrial and commercial companies, and estimate an elasticity to real GDP of +3.2 for Divisia M1 if inflation is not included in the long-run cointegrating vector, and +3.3 if it is. For Divisia M2, inflation is included and the elasticity of M2 demand to real GDP is +3.4. Drake & Chrystal select a rate they term the benchmark rate of interest as an opportunity cost, finding a long-run cointegrating semi-elasticity of -0.9 for the M2 equation, while including opportunity cost in a calculated variable in the M1 equations, yielding estimates of -4.8 and -4.3 respectively with or without including inflation.

Ericsson, Hendry & Prestwich [Ericsson et al., 1998] update the model of Hendry & Ericsson [Hendry and Ericsson, 1991] but continue to impose unit elasticity of money demand with respect to real GDP, basing a substantive part of their analysis on that assumption. Assessing demand for 'broad money' defined as a splice of M2, M3 and M4 at various points in time, they find the expected negative coefficient with respect to opportunity costs: -6.7 in this study, the 1991 study having estimated the semi-elasticity at -7.0.

Nielsen [Nielsen, 2007] considers a long time series beginning in 1873, and derives a long-run elasticity to real income of 0.77 for the same spliced measure of broad money employed in Ericsson *et al* [Ericsson et al., 1998]

– though the coefficient is statistically indistinguishable from 1 given the standard error of 0.145. Nielsen also reports an interest rate semi-elasticity of -7.7, highly comparable in magnitude with the findings of Ericsson et al.

Jawadi and Sousa [Jawadi and Sousa, 2013] consider the UK alongside the US and the Eurozone, and employ a quantile regression approach to capture nonlinearities – they report coefficients ranging from +1.76 to +2.04 to real GDP. Jawadi & Sousa employ M4 as their measure of money for the UK, and in common with Nielsen [Nielsen, 2007], they include inflation as a regressor despite measuring the monetary aggregate, and GDP, in real terms. This approach seeks to capture inflation as a separate opportunity cost to holding money, which is fixed in nominal value, as distinct from the increase in nominal value required to meet the transactional or utility motive in an inflationary environment. Were monetary aggregates expressed in nominal terms the expected sign to inflation might reasonably be expected to be positive, but in real terms inflation is another opportunity cost to holding money balances and should enter with negative sign – though in the work of both Nielsen [Nielsen, 2007] and Jawadi & Sousa [Jawadi and Sousa, 2013] it is more typically insignificant in long-run equilibria.

Other authors have included real effective exchange rates [Arize and Shwiff, 1993], alternative interest rates [Baba et al., 1992], measures of term and risk premia [Arize, 1994], and other explanatory variables in their functional forms – though to the best of our knowledge, no author has estimated a money demand function for shadow banking sector money using data from the United Kingdom, or estimated the relationship between shadow banking money and traditional monetary aggregates, as the present work proposes to do.

1.2.8 Money supply

In equating changes in observed quantities of monetary aggregates with changes in demand for money as all empirical studies outlined above do, the question of the role of money supply must be dealt with. Some of the above studies precede [Engle and Granger, 1987] , or incorporate data which precedes [Nielsen et al., 2004, Nielsen, 2007] , the recent consensus for central banks to target a policy interest rate rather than a monetary aggregate. In such studies it suffices to assume that the nominal supply of money is fixed – perfectly inelastic at the central bank's chosen quantity. It therefore follows that fluctuations in this total are due to changes in demand for money – though it should be noted that supply changes in response to *the central bank's perception of demand for money, and the assumption that this assessment is always and everywhere correct is a strong one.*

Since the 1990s, central banks have more often targeted a policy rate, normally along with a commitment to supply as many bank reserves as are demanded at that interest rate. Though in this paradigm the supply of central-bank-created money could be seen as being perfectly elastic at a given price – the policy rate – in practice the implications are the same. Fluctuations in the quantity of monetary aggregates observed result from changes in demand by holders of money, not idiosyncratic shifts in supply.

In examining the role of the shadow banking sector in supplying safe-asset substitutes for money, we will follow Pozsar [Pozsar, 2013] and view the supply of alternative, non-shadow-bank-produced safe assets as inelastic, and so attribute fluctuations in quantity of observed shadow banking sector liabilities to changes in demand for those claims.

1.2.9 Chapter conclusion

This chapter has briefly reviewed the history and nature of money, established the existence of financial intermediation as a response to imperfections in credit markets, surveyed the channels by which monetary policy impacts the real economy, and summarised the empirical literature concerning money demand, as well as highlighting common assumptions in the literature regarding money supply. It will be seen that understanding the functioning of credit markets is important for monetary policymakers and consequential for the real economy, and we turn now to more closely examine the nature of shadow banks and their role in these credit markets.

Chapter 2

Literature Review

2.1 Introduction to Shadow Banking

The term 'shadow banking' is acknowledged to have been coined as recently as 2007, by bond fund PIMCO's Chief Economist Paul McCulley [McCulley, 2007]. McCulley characterises the system, not unjustifiably, as an "alphabet soup of levered-up non-bank investment conduits, vehicles, and structures", and expresses concern about runs in the system, restricted access to liquidity, and the dependence of institutions within the system on implicit or explicit credit guarantees from parent institutions, often regulated banks. (For exposition: it is commonplace amongst practitioners in this field, and to an extent among academics studying it, to use the financial derivative market terminology 'put' for a credit guarantee provided by a linked or separate institution. In options trading, a put conveys the right but not the obligation to sell an underlying asset for a prearranged 'strike' price, and as applied to liabilities of the SBS, may be understood to mean the expectation that the guaranteeing institution will intervene to maintain a prearranged value of the security in question or its issuer- an example would be a credit line offered by a regulated bank to its own off-balance-sheet Special Purpose Vehicle, of which more below).

This chapter will survey the shadow banking system, incorporating motives for the existence of shadow banks, estimates of the scale of shadow banking activity globally, the structure and function of the financial instruments used by the shadow banking system, and a review of the empirical literature.

2.1.1 Form & function

The function of shadow banks, as the name implies, is similar to that of regular banks – they conduct credit transformation, liquidity transformation, and maturity transformation, albeit often by different means to regulated banks. Credit transformation involves the enhancement of debt quality of existing loans by application of a strict priority of claims – thus, senior tranches (layers) of risky debt are safer than a part share of the whole pool of loans, as some loans at least are always expected to perform, and the senior tranches have first claim to any revenue resulting from servicing those loans [Adrian and Ashcraft, 2016]. Credit can be enhanced to the point that senior tranches are acceptable even to risk-averse investors such as pension funds. Banks perform this role with deposit contracts, and by staking their own balance sheet as collateral and relying on public trust in their reputation, whereas shadow banks often use securitisation – pooling and slicing of loans- to make priority of claims explicit. As we have already seen, confusion around priority of claims can lead to bank runs, as in [Diamond and Dybvig, 1983]. It might seem then that shadow banks can use securitisation methods to clarify priority of claims, but as will be seen, confusion over the true allocation of risk may not be eliminated.

Maturity transformation in the shadow banking context is the use of short-term liabilities to fund long-term assets. Entities are rewarded for assuming maturity risk by the positive slope of the yield curve- long term loans pay a higher interest rate throughout the life of the loan, allowing the capture of a spread highlighted by the colloquial '3-6-3 rule' of traditional retail banking – borrow at 3%, lend at 6%, be on the golf course by 3pm. Shadow bank access to securitisation techniques allows for maturity transformation in either direction by credit intermediaries, and may lead to a more optimal pattern of maturity risk sharing, while a regular bank must assume the whole maturity risk of a loan it chooses not to securitise, sell or otherwise fund.

Liquidity transformation refers to the use of liquid liabilities to fund illiquid assets, and is one of the frictions FIs can solve in the microeconomic models discussed above- a surprise need for liquidity by consumers, who otherwise would not invest in value-adding projects [Adrian and Ashcraft, 2016]. Regulated banks are able to access government backstops to allow liquidity risk to remain on balance sheet, whereas shadow banks rely on their ability to roll their liabilities to fund their illiquid assets, for example in the repo markets [Acharya et al., 2011]. Entities are often rewarded for assuming liquidity risk by a liquidity premium in the interest rates paid, and though liquidity transformation and maturity transformation often go hand-in-hand, they are distinct services- a 30-year government bond, for example, has long maturity but is likely to be easier to sell and thus more liquid than a short-dated over-the-counter derivative referencing a specific named entity.

Shadow banks are thus able to perform the traditional banking roles with the potential to achieve a superior and more easily calculable allocation of risk through securitisation techniques- indeed much activity denoted as shadow banking is in fact performed by regulated banks when such precision is needed. Regular banks have advantages stemming from their government backstops- enabling them to plausibly guarantee riskier propositions- their large balance sheets, and their ability to share information and cross-sell between business lines.

Shadow banking however is not universally, or even typically, seen as benign. Portes [Portes, 2018] highlights the interconnectedness of shadow banks with the regulated banking system with potential for contagion, and many authors [Adrian and Shin, 2009a, Pozsar, 2014, Plantin, 2014, Huang, 2018] focus on the role of the sector in precipitating the recent Global Financial Crisis. As will be seen, significant gaps remain in our understanding of the scale of the shadow banking system (particularly outside the US), as well as the economic behaviour of the sector. Addressing these gaps is of importance for prudent financial policymakers in addition to being consequential for the real economy through the influence of shadow banking on the transmission channels of monetary policy.

2.1.2 Motives for Shadow Banking

Adrian and Ashcraft [Adrian and Ashcraft, 2016] offer the following three reasons why the shadow banking sector exists:

1. Innovation in the composition of aggregate money supply: Gorton and Metrick [Gorton et al., 2010] view the development of shadow credit intermediation as "financial innovation in the composition of aggregate money supply" [Adrian and Ashcraft, 2016]. The fractional reserve banking system, as depicted in the paradigm of Bryant [Bryant, 1980] above, does not maintain sufficient currency to make good all depositors' claim should they all be redeemed at once, and so bank deposits function as a money in their own right, limiting the need for specie. Initially backed only by general (typically illiquid) assets of the bank, these monies were subsequently guaranteed in the US financial infrastructure by the clearinghouses and later by the Federal Reserve System to ensure they traded at par with physical currency. Bank runs result when the convertibility of bank deposits into currency is uncertain. Deposit insurance can help to prevent bank runs by effectively stopping the run before it starts, often without the insurance ever needing to pay out. Money Market Mutual Funds (MMMFs) arose as a response to the limits on interest paid on checking accounts as well as account balance limits to this deposit insurance, typically investing in overnight repos collateralised by US Treasuries [Adrian and Ashcraft, 2016]. Recent work by Serletis & Xu [Serletis and Xu, 2019] is premised on the role of the shadow banking sector in providing banking services – taking deposits and making loans.

2. Capital, tax and accounting arbitrage: The access enjoyed by large banks to official liquidity support and guarantees poses a moral hazard problem. A promise of government bailout will engender excessive risk taking unless accompanied by minimum capital and liquidity standards – suggesting that the guarantees are mispriced, as equilibrium capital ratios would be below the regulated level. By moving capital-burden-attracting items off balance sheet without any real risk transfer, regulated banks can capture the full value of this positive

externality, and the shadow banking sector provides the mechanism to accomplish this [Adrian and Ashcraft, 2016]. Recent work by Adrian & Jones [Adrian and Jones, 2018] also cites mispriced sponsor backstops, in addition to regulatory arbitrage, as a key motive for shadow banking activity.

3. Agency problems in financial markets: Ashcraft and Schuerman [Ashcraft et al., 2008] identify seven key frictions in securitised loan markets: between mortgagor and originator, originator and arranger, arranger and third-parties (warehousers, asset manager, credit ratings agencies), servicer and mortgagor, servicer and third-parties, asset manager and investor, and investor and credit ratings agencies. Of these, the first two concern predatory borrowing or lending, the third concerns adverse selection, the fourth and fifth concern moral hazard, the sixth is a principal-agent problem and the seventh concerns model error. These seven frictions broadly correspond to Pozsar *et al*'s seven stages of shadow credit intermediation as will be seen below [Adrian and Ashcraft, 2016].

2.1.3 Categories of Credit Enhancement

The seminal reference in offering a taxonomy of shadow banking entities and their function is Pozsar *et al* [Pozsar et al., 2010]. Pozsar and co-authors define financial intermediaries based on the nature and extent of their access to credit backstops (synonymous with guarantees/puts as defined above), their role in the securitisation chain, and their relation to regulated FIs and to the government.

- Direct Official: balance sheet items that enjoy direct official enhancement are typically liabilities of regulated banks. This is the highest form of credit enhancement, but these instruments do not form part of the shadow banking sector.

- Direct Implicit: the Government-Sponsored Enterprises (GSEs) in the US, including for example Fannie Mae and Freddie Mac, benefit from "an implicit credit put to the taxpayer". The US government is the ultimate guarantor of the mortgages guaranteed by the GSEs, and most authors do not consider these entities part of the shadow banking system – though some, such as Pozsar *et al* [Pozsar et al., 2010] , do.

- Indirect Official: Off-balance-sheet liabilities of regulated banks are deemed to enjoy this form of enhancement, as the regulated bank has access to public sector support to make good on its obligations, including any credit lines or guarantees extended to associated off-balance-sheet entities, though these entities are not directly insured by the government. It is this part of the shadow banking sector that is frequently seen as arising from regulatory arbitrage.

- Indirect Implicit: includes bank-affiliated hedge funds and Money-Market Mutual Funds (MMMFs) operated by regulated institutions. These vehicles benefit from association with regulated banks but "may not benefit from such enhancement ex post". Such confusion about true risk allocation may only be revealed during times of financial market turmoil [Gennaioli et al., 2013].

- Unenhanced: Institutions in this category are not generally believed to benefit from any enhancement over and above their own creditworthiness.

2.1.4 The Seven Steps of Shadow Credit Intermediation

Source: [Adrian and Ashcraft, 2016, Pozsar et al., 2010]

- Loan Origination: performed by finance companies who issue Commercial Paper (CP) or Medium Term Notes (MTNs).

- Loan Warehousing: conducted by single- or multi-seller ABCP conduits.

- Asset-Backed Securities (ABS) Structuring: Broker-dealers' ABS desks syndicate and pool ABCP into tranched ABS.

- ABS Warehousing: ABS tranches are held on trading books, financed by Repo or Total Return Swaps (TRS).

- CDO Structuring: Broker-dealers may structure ABS into Collateralised Debt Obligations (CDOs) with agency-issued credit ratings, making them acceptable to e.g. pension funds, mutual funds.

- ABS Intermediation: Limited-Purpose Finance Companies (LPFCs), Structured Investment Vehicles (SIVs), Special Purpose Vehicles (SPVs), Securities Arbitrage Conduits, Credit Hedge Funds and other bank and non-bank affiliated entities fund ABS asset purchases with cash via repo, MTNs, bonds, equity or capital notes.

- Funding: All of the above steps are funded by wholesale funding market providers such as MMMFs, Enhanced Cash Funds, securities lenders and direct money market investors including corporate treasuries, fixed-income mutual funds, pension funds, and insurance companies.

2.1.5 The Four Shadow Banking Subcategories

Source: [Adrian and Ashcraft, 2016, Pozsar et al., 2010]

- The Government-Sponsored Shadow Banking Subsector: analogous to the classification of institutions enjoying direct but implicit credit enhancement above, the government sponsored SBS subsector is the securitisation chain whereby conforming mortgages are subsidised by the US Government through the GSEs.

- The Internal Shadow Banking Subsector: composed of the off-balance-sheet activities of regulated banks, the internal shadow banking subsector thus enjoys indirect but official credit enhancement.

- The External Shadow Banking Subsector: though independent of regulated banks and thus devoid of official credit enhancement, institutions of the external SBS are often affiliated with large non-bank financial or non-financial firms regulated in their own right, such as mutual funds, insurance companies, standalone broker-dealers, and the car finance subsidiaries of automobile manufacturers.

- The Independent Shadow Banking Subsector: whereas institutions of the external shadow banking subsector do not typically have shadow banking as their main activity, the independent shadow banking subsector comprises standalone MMMFs, standalone SIVs, and private label mortgage security structurers. Its credit would be characterised as unenhanced.

We summarize the four shadow banking sector subcategories and associate each with a motive and with a level of credit enhancement in Table 2.1. Reasons for existence are difficult to elucidate and frequently overlap, but this framework serves to guide our subsequent investigation into the data. In assessing the role of the shadow banking sector in producing money-like claims which may substitute for bank or government safe assets, our focus will be predominantly on the external and independent subsectors, with which we associate the motive of innovating in aggregate money supply. To the extent that financial aggregate data do not differentiate between 'internal' (bank-sponsored) and external money market mutual funds, there may be some overlap with the internal shadow banking subsector in our subsequent empirical work.

2.2 Developments in the shadow banking literature

The academic study of shadow banking began in earnest after the Global Financial Crisis of 2008 – though some authors have argued that the pre-central-bank era of Bagehot, when capital market financing was predominant, has much in common with the recent practice of shadow banking [Mehrling et al., 2013] . The early papers of Adrian & Shin [Adrian and Shin, 2009a, Adrian and Shin, 2009b] predominantly concern themselves with regulatory and policy issues, while the work of Pozsar and co-authors [Pozsar et al., 2010, Pozsar, 2013, Mehrling et al., 2013, Pozsar, 2014] has focused upon defining and giving a taxonomy of shadow banking system entities. Gorton & Metrick [Gorton and Metrick, 2009, Gorton et al., 2010, Gorton and Metrick, 2012] have written extensively about safe assets and in par-

Table 2.1: The four shadow banking sector subcategories

SBS Subsector	Key institutions	Level of credit enhancement	Proximal reason for existence
Government-sponsored	GSEs, ABS broker-dealers, MMMFs	Direct implicit	Agency problems
Internal	SIVs, SPVs, internal credit hedge funds, internal MMMFs	Indirect official	Regulatory arbitrage
External	ABCP conduits, insurance firm floats, hedge funds	Indirect implicit, or unenhanced	Innovation in composition of aggregate money supply
Independent	LPFCs, ABS warehousers, repo lenders	Unenhanced	Innovation in composition of aggregate money supply

ticular the repo markets at the heart of the shadow banking system. The literature as it stands is somewhat US-centric – early efforts focused on establishing the need for better regulatory and policy-making datasets to be collected [Pozsar, 2014] , with the result that the Financial Stability Board began to publish an annual Global Shadow Banking Monitoring Report in 2011 [Board, 2012] . More recent work has begun to consider the shadow banking system as an economic entity, assessing activity through theoretical [Gennaioli et al., 2013] , computable general-equilibrium [Verona et al., 2013, Nelson et al., 2015] or data-driven empirical [Duca et al., 2014, Serletis and Xu, 2019] approaches. Outside of the US, most authors have sought to start by estimating the magnitude of shadow banking activity in the geographic area of interest – we now turn to review these studies in more detail.

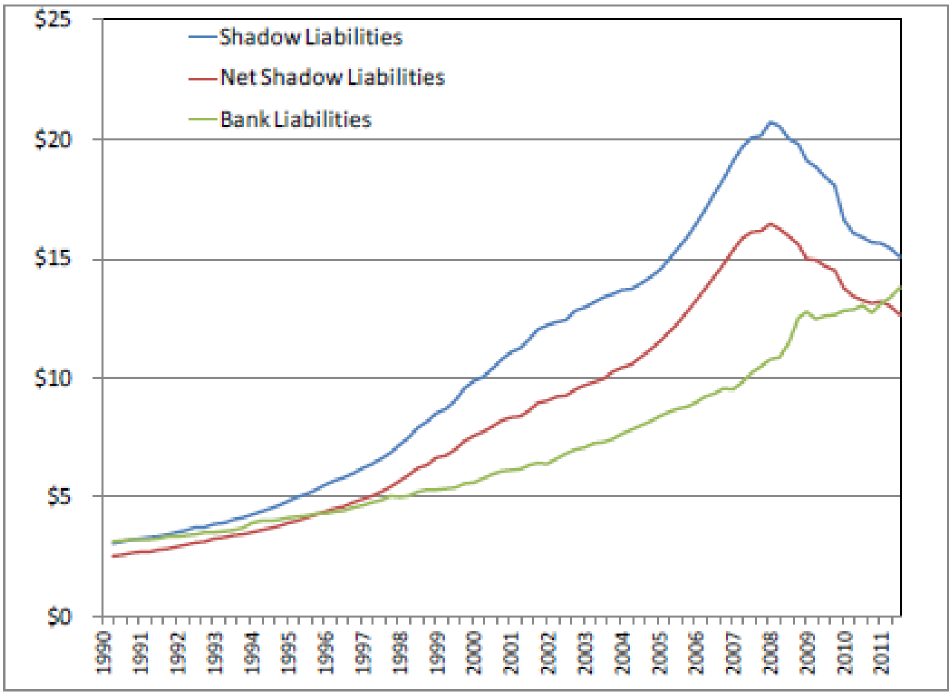
2.3 Sizing the shadow banking sector

The competing definitions and varying affiliations, regulatory regimes and jurisdictions of the institutions involved in shadow banking activity render a centralised database of shadow banking activity a virtual impossibility. Attempts have been made recently to estimate the size of the shadow banking sector under various definitions and employing diverse methods, and a selection are detailed below.

2.3.1 The U.S.A.

The comprehensive Federal Reserve Flow of Funds (FFoF) data in the US allow most attempts to size the American SBS to proceed in a conventional, balance sheet accounting manner. Thus [Adrian and Ashcraft, 2016] estimate the sector to have issued 28% of the aggregate money supply in 2011, having peaked at 45% in the early 2000s. They further estimate shadow institutions to own 31% of total financial sector liabilities and 55% of total credit transformation in 2011, from respective peaks of 36% and 60% in 2007/2008 [Adrian and Ashcraft, 2016]. [Pozsar et al., 2010] offer dollar amounts of liabilities, and estimate the sector at \$15tn in 2011:Q3, a

Figure 2.1: U.S. Shadow Bank and Traditional Bank liabilities



[Pozsar et al., 2010]

decline from a 2007:Q2 peak of $22tn, and consistently larger than the regulated banking sector, which peaks within the time series at $14tn in 2011:Q3 (Figure 2.1). The most recent Global Shadow Banking Monitoring Report [Board, 2018] gives the scale of 'narrow measure' shadow banking as $51.6 trillion in 2017, of which 29% in the US and 4% ($2tn) in the UK. The FSB's narrow measure includes those entities judged by the FSB as presenting a run risk due to involvment in maturity transformation, credit transformation, liquidity transformation or leverage. The measure excludes entities consolidated into a banking group and thus enjoying implicit credit enhancement in addition to being subject to regulation by transitivity. As such the FSB narrow measure excludes many securitisation vehicles. As the present work is concerned with the UK, we do not reproduce other estimates of the size of the US shadow banking sector *in extenso here, but the interested reader is referred to Adrian & Ashcraft* [Adrian and Ashcraft, 2016].

2.3.2 The Euro area

ECB data being somewhat less centralised than the Fed Flow of Funds, estimates of the size of the European shadow banking sector are somewhat more sensitive to classification of items and institutions, and these "do not always have enough granularity to identify different kinds of financial intermediation and risk exposures" [Bakk-Simon et al., 2011]. The quarterly Euro Area Accounts (EAA) divide institutions into monetary financial institutions, insurance corporations and pension funds, and the residual category 'other financial intermediaries'. While this OFI category includes many institutions typically conceived as being part of the SBS, it also includes regulated investment funds- who are engaged in shadow banking but not uniquely- and excludes MMMFs, which appear under MFIs. Insurance companies and pension funds may also fund the SBS through repo transactions but it is not their principal line of business. Relatively recently, the Euro area has added monetary statistics covering positions and flows between the MFI and OFI sectors, and balance sheets aggregates for institutions involved in securitisation. Bakk-Simon et al [Bakk-Simon et al., 2011] estimate the assets of the TBS as MFI minus MMMFs, and the SBS as OFIs plus MMMFs, but minus mutual fund shares issued by funds other than MMMFs, and return a value of EUR 10.8tn by assets for the European SBS in 2011:Q2 against EUR 28tn for the TBS. Figure 2.2 gives a time series, and Table 2.2 breaks out some components of the SBS share.

Arquie & Artus [Arquié and Artus, 2012] also employ ECB data and note that financial lending corporations, (step 1 of the shadow credit intermediation procedure outlined above), are also absent from the OFI classification- so any estimates yielded must necessarily undersize the sector. Defined on credit extended, they report the euro area SBS as EUR 6tn, approximately 20% of the total euro area credit extension of EUR 29.7tn in 2012:Q2. They further report \$2.3tn in outstanding securitisation, dollar valued for comparability, as of 2012. By a total asset measure that differs from Bakk-Simon *et al* [Bakk-Simon et al., 2011], inasmuch as it includes securitisation but not ICPFs, they give a figure of EUR 9.8tn as a potential size of euro area SBS balance sheets in 2012:Q2; or 23% of total financial institution assets.

Figure 2.2: Euro Area SBS and TBS by assets, time series

[Bakk-Simon et al., 2011]

2.3.3 The U.K.

Tyson & Shabani [Tyson and Shabani, 2013] seem to adopt a particularly broad definition of the SBS, including hedge funds and private equity in addition to the normal McCullean 'alphabet soup' of securitising entities. They do not provide an estimate of the size of the sector in the UK by conventional means, but rather reason that all SBS entities to a greater or lesser extent interact with the market through regulated investment banks- from SPVs created as off-balance-sheet asset pools for the banks themselves, to hedge funds who utilise the banks' brokerage services and private equity firms who rely on investment bank leverage to complete corporate buyouts. Reasoning that the ratios of compensation to revenue and of revenue to assets are both reasonably stable over space and time, Tyson and Shabani [Tyson and Shabani, 2013] proceed to estimate from publicly disclosed earnings and compensation statement the extent of off-balance-sheet revenues, and therefore assets. Applying the global ratios of 40.8% compensation: revenue and 3.7% revenue: assets for a stable long-term ratio of 2:5:135 compensation: revenue: assets, they derive £109bn estimated asset flow per

Table 2.2: Euro-area shadow banking sector breakdown

	2007 Q2: EUR tns	2007 Q2: % total	2011 Q2: EUR tns	2011 Q2: % total
Banks	25.6	54.0	28.0	51.5
Other intermediaries	8.5	17.9	10.8	19.9
of which Money market funds (MMFs)	1.2	2.5	1.1	2.0
of which Financial vehicle corporations	-	-	2.2	4.1
of which Other misc. intermediaries	7.3	15.4	7.6	13.9
Eurosystem	1.6	3.5	3.1	5.8
Investment funds other than MMFs	5.5	11.6	5.6	10.3
of which Hedge funds	-	-	0.1	0.2
Insurance corporations and pension funds	6.1	13.0	6.8	12.6
TOTAL ASSETS OF FINANCIAL INSTITUTIONS	47.3	100.0	54.4	100.0
Memo: Repo market outstanding value (lending and borrowing) in the EU	6.8		6.1	

annum, and a £546bn asset stock based upon an assumed 5 year average asset maturity. The assumption that these imputed ratios are stable over time is a weakness of the method, as is the arbitrary assumption of 5 year average maturity, but the result that off-balance-sheet assets are equivalent in size to 26% of on balance sheet assets corresponds sufficiently closely with the Eurozone estimates to appear plausible. The most recent FSB Global Shadow Banking Monitoring Report [Board, 2018] gives the 'narrow measure' of shadow banking for the UK as $1.9tn for 2017 – with the broader measure of assets held by nonbank financial corporates standing at $31.7tn for 2017.

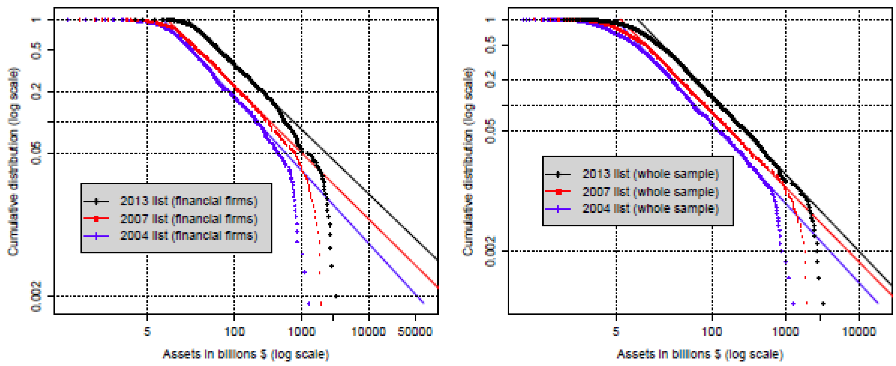
2.3.4 Alternative estimation methods

Fiaschi *et al* [Fiaschi et al., 2014] advance a further assumption-based estimate of the size of SBS globally. Firm sizes across countries and over time have been observed to obey a Paretian probability density function of the form:

$$Pr\{X \geq x\} \simeq cx^{-\gamma} \tag{2.1}$$

which is to say that the probability of observing a firm of size X larger than x is appoximately equal to x multiplied by a constant c, raised to the power of a scaling parameter $-\gamma$ – in other words, the probability of such an observation declines in constant proportion. The Paretian distribution is locally self-similar under appropriate scaling parameters, and gives rise to the 'Pareto principle', commonly known as the 80-20 rule- whereby 20% of some population control 80% of the distributed factor, often income or wealth. Such allocations can be characterised by a Pareto distribution for some γ (in the 80-20 case, $\gamma = \frac{log(5)}{log(4)}$). This constant-proportion property gives rise to a linear log-log plot, and Fiaschi et al note that the distribution of firm sizes obeys an appropriately-specified Pareto distribution for moderate values, and deviates at higher values, almost all of which represent financial firms (Figure 2.3). The implication is that these financial firms have unobserved assets whose inclusion would restore the observed distribution to the expected, and that these assets exist off-balance-sheet in the

Figure 2.3: Cumulative Distribution for of financial and all firms by assets



[Fiaschi et al., 2014] Cumulative distribution $Pr(S \geq x)$ for asset sizes S for financial (left panek) and all (right panel) firms in 2004, 2007, and 2012. The straight line is a linear fit in an intermediate range of $logPr(S \geq x)$ vs $logx$.

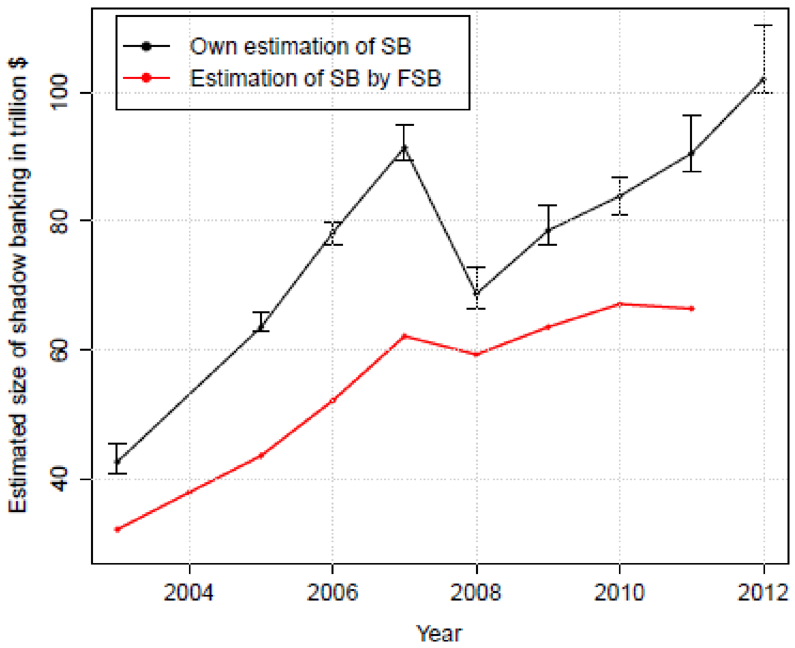
SBS.

Deriving an expected Pareto exponent of 0.905 for all firms in 2013 and 0.648 for financial firms only in 2013, Fiaschi *et al* [Fiaschi et al., 2014] obtain an estimate of over \$100tn for the size of SBS globally in 2012, compared to Financial Stability Board (FSB) estimates of \$65 - \$70tn (Figure 2.4). As common as such firm size distributions have been observed to be, there is of course no deterministic reason why financial firm sizes would obey this distribution, and examples of unexpectedly inconstant second or higher derivatives abound in financial economics (for example the 'volatility smile' of option theory).

2.4 Shadow banking in practice

Having considered broad metrics of shadow banking activity, this section will consider in more detail the specific financial instruments used by the shadow banking sector. From this consideration we will justify the selection of variables measuring shadow banking activity, to be used in the empirical work in Chapters 4 & 5.

Figure 2.4: Comparison of the Fiaschi *et al* Shadow Banking Index with FSB estimates



[Fiaschi et al., 2014] Confidence bands ±2 standard errors in Pareto exponent estimates.

2.4.1 Sale and repurchase orders

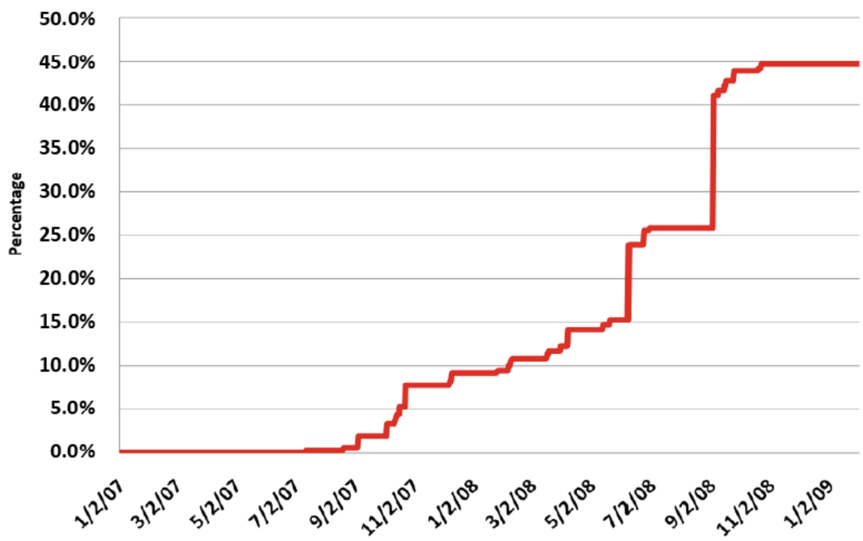
A sale and repurchase order, or repo, is a transaction involving the exchange of cash for collateral in the form of securities, with a promise to reverse the sale at the maturity date – frequently the following day. The amount paid in cash and the amount returned differ by the repo rate – a form of interest rate; and frequently less cash is provided than the market value of the securities pledged – this is known as the collateral haircut. For example if £80 cash is exchanged for £100 worth of securities and the securities are returned at maturity for £88, the repo rate is 10% $\frac{88-80}{80}$ and the haircut is 20% $\frac{100-80}{100}$.

Repo transactions can be bilateral, transacted directly between the cash provider and the collateral provider; or may involve a central clearing counterparty, known as the tri-party repo market. Repo transactions can thus arise both from a need for cash, mimicking a short-term secured loan, or from a need for securities e.g. for short-selling.

Adrian *et al* [Adrian et al., 2013] find that the tri-party repo market is mostly driven by the cash side, particularly as the cash provider does not have to process the securities collateral in its own back office – meaning a more diverse range of counterparties and wider use of non-specific General Collateral. At the centre of the tri-party repo market in the US are the clearing banks, JP Morgan and Bank of New York Mellon. The tri-party market is a key source of funding for securities dealers, and cash is provided by a wide array of firms with MMMFs accounting for 25-30% [Adrian et al., 2013].

The bilateral market exists to serve parties who wish to transact specifically with one another or in a specific security, and so is better configured for collateral lending rather than cash lending transactions [Adrian et al., 2013]. Collateral pledged in repo transactions can be rehypothecated- used as collateral in a further lending transaction- meaning that the haircut mathematically functions as a limit on leverage; for some constant haircut θ, leverage by rehypothecation is limited to $\frac{1}{\theta}$ [Copeland et al., 2014]. An increase in haircuts- meaning the same collateral can secure less cash- results in a funding shortfall that can prompt fire sales of the assets, pushing down collateral prices, increasing haircuts and exacerbating the situation, as

Figure 2.5: The Haircut Index of Gorton & Metrick



[Gorton and Metrick, 2009] Formatting per original.

depicted in Figure 2.5 (drawn from Gorton & Metrick [Gorton and Metrick, 2009]).

The size of the repo market in the US is typically estimated at around \$3tn, of which \$2tn is in the tri-party repo market and the balance in bilateral repo [Martin et al., 2014, Adrian et al., 2013]. The role of repo in the shadow banking sector is as the deposit analogue; repo offers a repository for corporate, insurance and mutual fund cash piles that is secured rather than insured, and offers some yield. Thus demand for repos arises for two distinct reasons; firstly a search for a money-like instrument for value storage and to meet liquidity needs, and secondly a search for low-risk yield. The former is characteristic of corporates and insurers with cash balances larger than the deposit insurance limit, while the latter is more typical of mutual funds and hedge funds (HFs) [Pozsar, 2014].

Repo may be viewed then as part of the growing debate on private vs public money creation, the Bank of England having recently officially acknowledged the view commonly held for some time, that the majority of money creation is enacted privately in the form of bank deposits and comparable liabilities [McLeay et al., 2014]. Empowered to create money as they see fit, commercial banks will nevertheless only do so when profitable lending opportunities exist, raising the possibility that when cash seeking deposit contracts outstrips the availability of profitable lending opportunities, repo may constitute an additional source of private money to meet this demand [Pozsar, 2014]. Sunderam [Sunderam, 2014] advances a theoretical model of the SBS as meeting demand for private money-like assets which also offers empirical support for the proposition.

The value of money, privately or publicly created, always and everywhere relies on confidence that it will be accepted and trade at or near par- for sovereign currency-issuing entities, this amounts to a promise to control inflation. For banks and shadow banks, this value promise rests on the pool of assets backing the money liability – and if banks lend to all profitable lending opportunities and back their deposit liabilities with this mixture of whole loans, then we may conclude that one of the functions of the SBS is to make unprofitable lending opportunities profitable, at least for some participants in the capital structure. This attempt to guarantee the value of privately-issued money drives the requirement for MMMFs, the depository institutions of the SBS, to maintain the Net Asset Value of each of their \$1-face-value shares above \$0.995- failure to do so is known as 'breaking the buck', and, as with uncertainty around the ability of banks to make good their deposit contracts, can lead to a run on the system.

Martin, Skeie and von Thadden [Martin et al., 2014] derive a Diamond-Dybvig style model in which repo runs results from liquidity shocks as per [Diamond and Dybvig, 1983], but also from collateral shocks. Copeland *et al* [Copeland et al., 2014] complement this theoretical work with an empirical piece which also serves to highlight the differences between the bilateral and tri-party repo markets during the financial crisis- the bilateral markets suffered haircut spirals, whilst haircuts in the tri-party markets remained largely stable but volumes dropped precipitously in a number of cases. The tri-party response thus resembles a 'classic' bank run, while the bilateral response displays an attempt to adjust prices rather than quantities- albeit in an extreme sense- rendering the transactions more security-like and less money-like. Acharya, Gale & Yorulmazer [Acharya and Naqvi, 2012] advance a collateral-constraint based model, and show that in the presence of rehypothecation and buyers who also need to finance their portfolio, small doubts about the value of the collateralising security (corresponding to small changes in the Markov chain state transition probabilities) can lead to large drops in the debt burden that security can sustain.

2.4.2 Asset-backed commercial paper

Asset-backed Commercial Paper forms the intermediate security of SBS intermediation chains. Short-term commercial paper backed by a specific pool of cash flow-generating assets, ABCP is typically issued by a special-purpose vehicle established by, but independent of, the originator of loans. The originator transfers ownership of the assets into the SPV, meaning they and their cash flows are isolated from the originator in case of the originator's failure. ABCP claims can therefore maintain their value as long as their specific assets continue to perform, whereas the failure of a bank's general asset pool can impair all of its retail deposits. ABCP also plays a role in maturity transformation, as its reference assets are typically ABS of 3 to 5 years' maturity while the tenor of the ABCP itself can be anything from one to 180 days, but typically around 30 days [Adrian and Ashcraft, 2016, Acharya et al., 2013]. Designed as a mechanism for more accurate and controllable allocation of cash flows and associated risks, ABCP is considered by Acharya *et al* [Acharya et al., 2013] to exist almost solely for regulatory arbitrage – credit guarantees provided by regulated banks to ABCP conduits require much less capital to be held against them, enhancing banks' return on equity. Acharya *et al* [Acharya et al., 2013] show that more capital-constrained banks were more likely to establish conduits; and in the event that these conduits were strained, it is shown that losses accrued substantially to the banks guaranteeing them rather than the investors purchasing the ABCP issued. This is consistent with little or no economic risk transfer taking place [Acharya et al., 2013]. Kashyap *et al* [Kashyap et al., 1992] show that borrower firms also treat commercial paper as an imperfect substitute for bank loans, issuing more when monetary conditions are tight, suggesting that a reduction in bank loan extension is not the result of falling demand from borrower firms, but lower willingness to extend credit on the part of banks. The regulatory arbitrage associated with ABCP conduits may therefore allow for extension of credit that would not otherwise have take place – though as this may take place at a time of tight monetary policy, for the benefit of a firm of questionable creditworthiness and by a bank of questionable strength, it is doubtful how welfare-enhancing such credit provision is.

2.4.3 Asset-backed securities

Asset-backed securities are a general class of bond-like entities representing claims on pools of loans, mortgages or receivables [Adrian and Ashcraft, 2016]. Whereas the pool of whole loans will have varying interest rates and payment times, pooling and tranching can impose regularity on these cash flows to produce a collateralized bond with regular fixed coupon payments, collateralised by the underlying. The process of packaging loans into ABS is known as securitisation, and results in tradeable, and therefore more liquid, claims- potentially improving risk allocation. ABS issuance is however principally a process of credit enhancement by diversification- using historical or projected default rates, the ABS can be issued in slices known as tranches, with ordinal seniority of claim and eligible for credit rating by ratings agencies such as Standard & Poor's or Moody's. The first defaults are absorbed by the equity tranche typically retained by the issuer, the mezzanine tranche may attract a junk-bond level rating and its high coupon attracts hedge funds, while the super-senior tranche has first claim on any cash flows and can therefore often attract an investment grade rating- rendering it eligible for purchase by pension funds etc. ABS's credit enhancement facility being based substantially on diversification, default probabilities are highly sensitive to model risk in general and the correlation parameter in particular- the chance that a loan will default given that other, similar loans are defaulting. This correlation results from similar loan notional values with similar interest rates likely being issued to borrowers with similar characteristics.

David X., Li's canonical copula formulation [Li, 2000] generalises the standard, discrete definition of correlation of two random variables to continuous distributions common to actuarial science- the survival function, its complement the failure time function, and the instantaneous failure rate as time tends to zero, known as the hazard rate function. Nevertheless this 2000 publication surveys properties of copula functions in general, with a few specific examples, and notes that the selection of copula function depends on assumptions about the marginal distributions of the underlying variables- it seems a little harsh therefore to brand the Gaussian copula function 'the formula that killed Wall Street' [Salmon, 2012] when the inadequacies of the bell curve for accurately representing payoffs of financial assets are well documented [Hudson and Mandelbrot, 2008].

It will be seen then that each financial entity in the SBS specialises to an extent in one of the driving motives for SBS, and one for FI in general- repo markets thus exist to serve a need for money and liquidity transformation, ABCP offers regulatory arbitrage but also aids maturity transformation, while ABS's role in credit transformation also helps address information problems in financial markets. Perversely, one of the ways it does this is not through transparency, making the value of investment projects easier to ascertain, but rather making this process harder in the quest for what Dang *et al* [Dang et al., 2017] refer to as 'optimal opacity'. Their Diamond-Dybvig style model shows that banks can improve allocative efficiency by obscuring information about the quality of their assets, so that the bank money issued with these assets as backing does not fluctuate in value, adding friction to trade. They show that under their conditions, banks will invest in information-insensitive assets to reduce the incentive to produce private information about the projects that could prove damaging to the value of the bank's money, while capital markets will directly finance projects that are sufficiently risky or where the cost of producing information is sufficiently low.

A wide literature concerns the decision facing firms to seek bank finance as opposed to capital markets finance. Fama [Fama, 1985] famously asked 'What's Different About Banks?', referring to their need to finance interest forgone on capital held in reserve by increasing interest rates on loans, creating a paradox whereby loan clients should optimally select alternative providers to receive financing at lower rates. Bolton & Freixas [Bolton et al., 2012] show that under specified conditions a banking sector and capital markets can coexist, with bank loans preferred by risky borrowers and lower-risk clients preferring capital markets- further implying lower interest rates in the open market. Biswas & Koufopoulos [Biswas and Koufopoulos, 2014] show that banks can offer underwriting services to capital markets issuers, backed by reserves to reassure borrowers that their guarantees are trustworthy and helping positive NPV projects to attract funding. Of the empiricists, Duca's vector error-correction model shows that activity in the shadow banking sector is strongly driven by constraints on the TBS- reserve requirements, deposit interest rate ceilings, prop trading restrictions and others cause the financial system to seek alternatives outside the government-guaranteed sector [Duca et al., 2014].

2.5 The demand side

Most national statistical authorities publish multiple monetary aggregates with different financial instruments included or excluded. In the UK these are the narrow money measure M0, composed of notes & coins as well as central bank reserves, and the broad money measure M4 including M0 in addition to sterling bank deposits, certificates of deposit, commercial paper, bonds, floating-rate notes, repo claims on UK regulated banks, sterling bank bills, and other instruments of up to 5 years' maturity issued by UK banks. The consumer demand theory approach identified with the Chicago school [Sriram, 1999] recognises that different elements of monetary aggregates are not, in practice, treated as perfect substitutes- and that these elements may be weighted by applying a factor $w_i \in \{0, 1\}$ known as the element's 'moneyness' for all $i = (1, 2, \dots, N)$ elements of those monetary aggregates. Moneyness, as a proportion relative to cash=1, measures the extent to which the asset performs the function of money- formally, they are entered "as inputs into the production function of money services" [Sriram, 1999]. This measure therefore defines the extent to which assets are used, in practice, as money substitutes though not perhaps the extent to which they resemble money in the abstract. One could imagine a moneyness measure defined over the characteristics of money as a store of value- liquidity, safety in the form of a realising full nominal value almost surely, ubiquity, acceptability etc. It is this moneyness-as-value-store measure that non-specie money-like claims of the TBS and SBS seek to maximise. Insured bank deposits attain a high moneyness 'score' under both definitions, with bank account balances frequently (in fact in overwhelming majority) transferred to settle transactions in lieu of currency. SBS money-like claims, whilst infrequently used transactionally, nevertheless attain a high theoretical-moneyness measure- repo transactions, for example, are settled daily offering high liquidity, and are overcollateralised (to the extent of the haircut) by mutually acceptable securities that possess an automatic 'stay' in case of counterparty bankruptcy, allowing the cash lender to retain the collateral in the event that the cash balance is unable to be repaid with interest [Gorton et al., 2012]. Money-market mutual fund shares are constrained to be redeemable at par at all times, and investors must be informed if the net asset value of the fund falls below \$0.995 per \$1 invested. Money-market deposit accounts, though operated by the TBS, are active in repo and securitisation markets and can be used identically to bank deposit or checking accounts.

It is these characteristics of SBS claims that the demand-side literature highlights – liquidity, safety, and only secondarily enhanced yield. Gorton *et al* [Gorton et al., 2012] document that the proportion of all US financial assets considered 'safe' has remained relatively constant at around 33% since 1952, whilst the ratio of total assets to GDP has increased by a factor of 2.5- implying a role for safe assets in the production of total assets, or a technology that allows only this proportion of total assets to be, or be made, safe at any one time. Furthermore, the composition of this safe asset share has changed over time, with government liabilities and traditional insured bank deposits falling in proportion relative to SBS claims and investment-grade corporate bonds. Along with increasing GDP the result is a substantial increase in notional value of financial assets outstanding, a consistent proportion of which are nevertheless considered likely to be redeemable at nominal par value.

Pozsar [Pozsar et al., 2010] attributes some of this demand to US corporate treasuries, pools of cash held for liquidity management reasons and invested in a range of safe assets including bank deposits, government debt and repo & securitised instruments. Being above the insurable margin with an average cash pool magnitude in this paper of $15bn, corporates derive risk limitation benefits from diversifying across financial firms and asset types, limiting their exposure should a single counterparty fail to redeem its liabilities. Corporates will also utilise derivative trades to manage specific business risks, and likely maintain cash or liquid positions to meet fluctuations in the margin accounts such derivative trades require. Pozsar [Pozsar et al., 2010] assigns to these corporate cash pools $2.2tn of safe asset demand at their 2007 peak, falling to $1.9tn by Q4 2010, of which $1.5tn was met by the SBS with the balance in TBS accounts and government bond portfolios. Sunderam [Sunderam, 2014], considering the safe asset demand attributable to households and individual savers, notes that ABCP issuance outstanding grew by 70% between 2004 and 2007, peaking at a notional outstanding value of almost $1.2tn in 2007. Krishnamurthy and Vissing-Jorgensen [Krishnamurthy and Vissing-Jorgensen, 2012], assessing the demand for Treasuries (US government bonds) and the effect on yields of other financial assets, show that Treasury yields were depressed on average by 72 basis points (0.72%) over the period 1926-2008 by this demand. They further show that supply of Treasuries negatively affects both the supply of bank-issued money, and the yield spread between bank money and less 'moneylike' safe assets- the fall of this spread suggests constrained Treasury supply induces lower yields on these assets, allowing them to become more moneylike [Krishnamurthy and Vissing-Jorgensen, 2012]. Finally, Bernanke *et al* [Bernanke et al., 2011] document total issuance of safe assets of the order $4.5tn in the period 2003-2007, of which 55% was sold to foreign investors including European banks and governments, Asian corporates, 'Global Savings Glut' countries where households tend to be net savers rather than borrowers (esp. China), and oil-rich Middle Eastern sovereigns. Supposing that the remaining 45% was sold uniquely to US corporates rather than households, this approximates the $2.2tn cited by Pozsar [Pozsar et al., 2010] to within an order of magnitude.

Serletis & Xu [Serletis and Xu, 2019] construct a sophisticated model of the role of the shadow banking sector in meeting demand for banking services in the US, and further hypothesis that the substitutability/complementarity between regulated bank and shadow bank services is vital in the transmission of monetary policy. They allow for Markov regime-switching, and document that the emergence of the shadow banking sector has increased the stability of money demand functions, concluding that measures of money supply may be more useful indicators of the stance of monetary policy than the interest rate.

2.6 Conclusion

Taken together this literature demonstrates a large and consistent demand from households, corporates and governments both US and foreign for assets considered safe. In the event that this demand cannot be entirely satisfied by traditional banks or government bonds – due to deposit insurance limits [Pozsar, 2013], fiscal prudence constraints [Sunderam, 2014], or because excessive government debt may cause such claims to lose their information-insensitive characteristic, thereby losing the very safety investors demand [Krishnamurthy and Vissing-Jorgensen, 2012] – the demand may be to an extent met by a shadow banking system that, by allocating or concealing risk, allows production of money-like assets from loans of varying quality.

We have reviewed the literature around shadow banking in some detail. Being US-centric, little work has been done focusing on the UK shadow banking sector specifically. Though hypothetical, descriptive and theoretical models of the role of shadow banking in meeting demand for safe assets have been advanced, no empirical models exist setting the UK shadow banking sector in the context of safe asset demand. We propose to gather UK data, construct measures of shadow banking sector activity, and plalce these measures empirically in a demand-for-safe-assets context. In considering shadow banking from the perspective of demand for safe assets, our empirical framework is close in spirit to the theoretical framework of Gennaioli *et al* [Gennaioli et al., 2013]. In assessing shadow bank services as substitutes for government debt, we take after Krishnamurthy & Vissing-Jorgensen [Krishnamurthy and Vissing-Jorgensen, 2012] , and in considering the substitutability between shadow bank and traditional bank services, we have much in common with Serletis & Xu [Serletis and Xu, 2019] and fit into the theoretical framework of Pozsar [Pozsar, 2013] – however the focus on the UK is novel.

Our results will be of interest to policymakers concerned with prudential regulation, as well as the transmission of monetary policy to the real economy given the shadow banking sector's role in the transmission mechanism as set out above. We now turn to formulate our hypotheses in detail, and introduce our dataset.

Chapter 3

Data and Hypotheses

3.1 Developing Hypotheses

The focus of the present work is upon the role of the shadow banking sector in meeting demand for money-like assets in the United Kingdom. Money-like assets are defined as those assets providing one or more of the monetary services outlined above, but in particular that of a store of value, and as such the present work also addresses the topic of demand for safe assets [Gorton et al., 2012], of which money-like assets are a subset. The framework for this analysis will be provided by the well-established literature concerning demand functions for existing published monetary aggregates, and a key contribution of the present work is to extend this framework to constructed aggregates of shadow banking sector monies. The remainder of this chapter aims to develop specific, testable hypotheses from the existing literature on the characteristics and dynamics of shadow banking.

H1: The demand function for shadow banking sector liabilities can be estimated under the assumption that competing safe assets have supply rigidities leading to inelasticity

To the extent that it is measurable, shadow banking activity can be presumed to share a relationship with broader economic activity. Shadow banking liabilities are demanded by rational economic actors, and as such it should be possible to empirically observe and econometrically estimate the relationship of the shadow banking sector to the broader economy. Golec & Perotti [Golec and Perotti, 2017] document the emerging importance of considering shadow banking sector instruments in the literature concerning safe asset provision. The assumption that substitutes such as government debt and bank deposits are inelastic in supply may be more valid in the short run.

H2: This demand function has characteristics comparable to well-established demand functions for exiting monetary aggregates

If indeed shadow banks provide monetary services, and their products are to an extent substitutable with money assets of the traditional banking sector, then it is to be expected that the demand function for shadow money shares characteristics with well-established demand functions for traditional money. That is to say, aggregate demand for SBS liabilities should be increasing as real GDP increases, and also increasing as its own rate of return increases. Demand is expected to be decreasing as the 'cost' of holding such money increases - typically defined as opportunity cost, i.e. a higher outside interest rate. Pozsar [Pozsar, 2013] documents the importance of the shadow banking sector in meeting demand for safe assets from corporate cash pools, whose demand stems chiefly from the transactional motive for holding money.

H3: Corporate cash pools are a key source of demand for shadow banking sector monetary services

In the prolific literature on shadow banking as a provider of private-sector monetary assets due to Pozsar and various co-authors [Pozsar et al., 2010, Pozsar, 2013, Pozsar, 2014], there are two key institutional 'bids' for SBS-created money - corporate treasurers searching for safety and fund managers reaching for enhanced yield. As the present work is concerned with safe asset provision, we focus on corporate cash pools as a source of demand - and hypothesize that demand for SBS liabilities should share a negative relationship with corporate assets deposited in traditional banks, all other things being equal. That is to say that a corporate treasurer's decision to place the marginal pound sterling in a traditional bank deposit should 'crowd out' the production of a shadow bank liability such as a money-market mutual fund unit to receive that pound. This assessment of substitutability/complementarity between traditional and shadow bank deposits builds on the work of Serletis & Xu [Serletis and Xu, 2019].

H4: As a safe asset, SBS liabilities are treated as a government-debt substitute

It is not only corporate cash pools who may treat SBS liabilities as a substitute for an alternative safe asset. Any investor seeking safety would likely also consider government-issued debt securities - though of course at sufficient scale, a cash pool may wish to diversify away from even the most creditworthy issuer in the economy, and not merely for reasons of enhanced return. Nevertheless, and considering Gorton *et al*'s [Gorton et al., 2012] finding that the safe asset share in the (US) economy is approximately constant, it might be expected that SBS safe assets and government-produced safe assets share a negative relationship at the margin. Krishnamurthy and Vissing-Jorgensen [Krishnamurthy and Vissing-Jorgensen, 2012] address this hypothesis at length for the US case, and find this hypothesis borne out in data covering the period 1914-2011. It should be noted however that their definition of private sector safe assets is broader and covers both what we would term 'traditional' and 'shadow' banking sector liabilities in a single set of aggregates.

3.2 Contribution of hypotheses to the literature

Should our hypotheses be borne out, a principal contribution will be to the shadow banking literature. We will have extended the work of Tyson & Shabani [Tyson and Shabani, 2013] by retaining their UK focus, and offer evidence for Pozsar's [Pozsar, 2013] work showing corporate cash pools as a key bid for shadow bank liabilities. The broader demand for safe assets perspective follows the work of Gorton & Metrick [Gorton et al., 2012], and

Table 3.1: Hypotheses

Hypothesis	Variable entering SBS money demand function	Expected sign and magnitude
H2	Log real GDP	+, approximately 1
H2	Own interest rate	+
H2	Opportunity cost / alternative interest rates	-
H3	Corporate deposits in traditional banking sector	-, around 1 in absolute magnitude if 'crowding out' is total
H4	Government debt outstanding, government debt issuance in short-run models	-, around 1 in absolute magnitude if 'crowding out' is total

the focus on substitutability of shadow bank money with government debt and bank deposits extends the work of Krishnamurthy & Vissing-Jorgensen [Krishnamurthy and Vissing-Jorgensen, 2012] and Serletis & Xu [Serletis and Xu, 2019].

The work also contributes to the broader literature on money demand in the UK, extending the work of Hendry & Ericsson, Drake & Chrystal, Ericsson *et al*, Nielsen, and Jawadi & Sousa [Hendry and Ericsson, 1991, Drake and Chrystal, 1994, Ericsson et al., 1998, Nielsen, 2007, Jawadi and Sousa, 2013].

Methodologically the work draws on the vector time-series paradigm of Johansen [Johansen, 1988, Johansen and Juselius, 1990] and the factor-based work of Stock & Watson and of Banerjee & Marcellino [Stock and Watson, 1999, Stock and Watson, 2002, Stock and Watson, 2005, Banerjee and Marcellino, 2009]. We also introduce a strategy for identifying long-run cointegrating vectors in a factor-augmented vector error correction model (FAVECM) which is believed to be novel. We now consider the data we will use to test these hypotheses.

3.3 Dataset description and UK Flow of Funds

3.3.1 Introduction

A notable contribution to the literature attempting to assess the scale and activity of the shadow banking sector in the United States is that of Errico, Haruyunyan, Loukoianova, Walton, Korniyenko, Amidzic, AbuShanab and Hyun Song Shin [Errico et al., 2014]. Working at the International Monetary Fund and making use of that institution's access to standardized financial reporting data provided by participant nation states, Errico *et al* create a Global Flow of Funds, mapping financial activity between economic sectors within and across borders. Their approach shares a thematic spirit with the Stock-Flow Consistent school of analysis latterly championed by the Post-Keynesian school of economics and Wynne Godley in particular, but dating back at least to Copeland's work of 1949, and arguably encompassing the MONIAC of Phillips. Phillip's MONIAC (Monetary National Income Analogue Computer) represented stocks and flows within the UK economy as reservoirs and pipes filled with water, and in a similar spirit, the Stock-Flow Consistent modelling tradition attempts to avoid 'leakages' – with every dollar or pound sterling leaving one sector, finding a destination in another. In the case of the United States as studied by Errico *et al*, this approach consists of a sectoral input-output matrix that they term the Balance Sheet Approach (BSA), and a matrix to capture the destination (origin) nationality of funding leaving (arriving) across American borders.

Errico *et al* initially offer a broad definition of the shadow banking sector resulting from this approach. Conjecturing that in normal times regulated banks depend mostly if not solely on domestically-sourced retail and small corporate deposits for funding, they argue that this stable but finite source of liabilities would be insufficient to support rapid asset growth during a lending boom. Therefore to allow balance sheets to expand more rapidly, traditional banks seek what Errico *et al* term 'noncore' liabilities – a category including foreign individual and corporate depositors in addition to the repo dealers and wholesale capital market lenders with whom we have identified shadow banking thus far. The broadest possible definition of shadow banking then, would be total liabilities of the regulated financial intermedi-

Figure 3.1: Matching Assets and Liabilities - the US example

Holder of claim (creditor) \ Issuer of liability (debtor)	Central bank			Central government			State and Local Government			Public Nonfinancial Corporations			Other Depository Corporations		
	A	L	NP	A	L	NP	A	L	NP	A	L	NP	A	L	NP
Central bank				57	1,657	-1,600	0	0	0	0	0	0	1,534	1	1,533
Currency and deposits															
...															
Central government	1,657	57	1,600										825	64	761
Currency and deposits															
...															
State and Local Government	0	0	0										726	568	159
Currency and deposits															
...															
Public Nonfinancial Corps.	0	0	0										0	0	0
Currency and deposits															
...															
Other depository corporations	1	1,534	-1,533	64	825	-761	568	726	-159	0	0	0			
Currency and deposits															
...															
Other financial corporations	79	23	56	11	3,033	-3,022	614	1,276	-663	0	0	0	3,920	2,453	1,467
Currency and deposits															
...															
Nonfinancial corporations	0	0	0										1,325	2,220	-895
Currency and deposits															
...															
Other resident sectors	927	0	927										6,812	8,770	-1,958
Currency and deposits															
...															
Nonresidents	160	160	-1	85	5,702	-5,617	0	0	0	842	1,418	-576	1,996	2,285	-288
Currency and deposits															
...															

Holder of claim (creditor) \ Issuer of liability (debtor)	Other Financial Corporations			Nonfinancial Corporations			Other resident sectors			Nonresidents		
	A	L	NP	A	L	NP	A	L	NP	A	L	NP
Central bank	23	79	-56	0	0	0	0	927	-927	160	160	1
Currency and deposits												
...												
Central government	3,033	11	3,022							5,702	85	5,617
Currency and deposits												
...												
State and Local Government	1,276	614	663									
Currency and deposits												
...												
Public Nonfinancial Corps.	0	0	0							1,418	842	576
Currency and deposits												
...												
Other depository corporations	2,453	3,920	-1,467	2,220	1,325	895	8,770	6,812	1,958	2,285	1,996	288
Currency and deposits												
...												
Other financial corporations				50	12,162	-12,113	21,151	8,630	12,521	5,747	6,919	-1,172
Currency and deposits												
...												
Nonfinancial corporations	12,162	50	12,113							9,298	5,416	3,882
Currency and deposits												
...												
Other resident sectors	8,630	21,151	-12,521									
Currency and deposits												
...												
Nonresidents	6,919	5,747	1,172	5,416	9,298	-3,882						
Currency and deposits												
...												

Source: IMF Statistics Department, BIS International Banking Statistics, U.S. Federal Reserve Board.

	Other financial corporations		
	Assets	Liabilities	Net position
Other depository corporations	2,453	3,920	-1,467
In domestic currency	2,453	3,920	-1,467
Currency and deposits	1,724	0	1,724
Securities other than shares	170	3,155	-2,985
Loans	558	656	-97
Shares and Other Equity		109	
Insurance technical reserves	0	0	0
Financial derivatives			
Other accounts receivable			
In foreign currency			
Currency and deposits	0	0	0
Securities other than shares	0	0	0
Loans	0	0	0
Shares and Other Equity		0	
Insurance technical reserves			
Financial derivatives			

sectoral/instrumental breakdowns not fully available

[Errico et al., 2014]

ation sector, minus household deposits in that regulated sector. Errico *et al* further attribute elevated or rapidly growing noncore liabilities with predictive power in anticipating financial crises – and more generally recommend that policymakers study the composition of banking sector liabilities as an indicator of financial conditions.

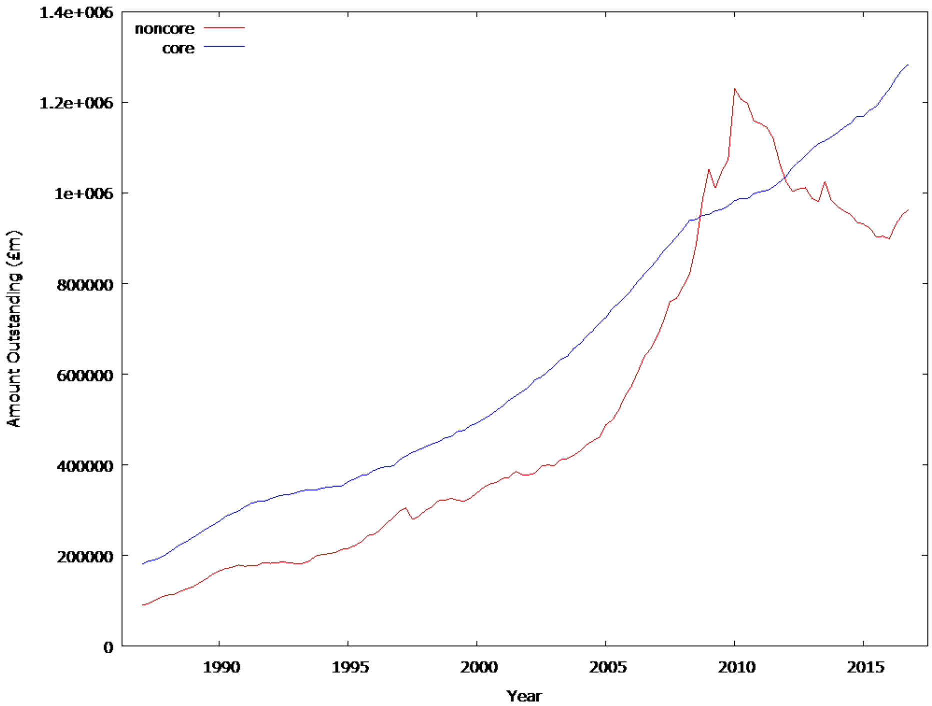
Notwithstanding their focus on shadow banking in the text, the method of Errico *et al* is comprehensive, matching assets and liabilities across 13 different types of financial instrument for each of 9 different economic sectors, for some 1,404 individual data points (or individual time series). That said, given constraints on data availability, their matrix is sparse – the US example provided in the original paper is reproduced herein as Figure 3.1.

Errico *et al* proceed to offer some description and analysis of the time-series behaviour of core and noncore funding in the US, along with empirical evidence in the form of panel regressions of various components of core and noncore funding on funding aggregates and macroeconomic variables for a sample of 82 countries. Eschewing vectorized systems and instrumental variables approaches in favour of simple OLS to estimate partial derivatives, Errico *et al* conclude that both core and noncore liabilities have significant positive correlation with within-country growth of loans to the private corporate sector – but not to the public sector. In their directions for further work, Errico *et al* note data availability as an important area for future focus, and highlight the UK in particular as a data gap – the UK at this time did not provide data to the IMF using standardized reporting forms.

The present work therefore set out to in some part replicate the method of Errico *et al*, and not without success. With our focus still upon shadow banking, we nevertheless considered the same 1,404 sector-instrument pairs considered by Errico *et al*, and though we faced similar data availability issues, were able to complete the matrix to a comparable standard. However, in the words of Laurence Fishburne's Morpheus from the prominent 1999 film, "nobody can be told what *The Matrix* is; you have to see it for yourself" – and to that end the full BSA approach matrix implemented for the UK by the author is available in a more accessible format in the online appendix at https://s3.eu-west-2.amazonaws.com/domsilman-thesis-technicalappendix/BSAMatrix.xlsx. We note that, subsequent to the present work being conducted, the UK statistical authority the ONS now publishes flow-of-funds matrices in accordance with the practice established by Errico *et al* – though at a much higher, more aggregate level. These data series are mostly sourced from the ONS – the contribution of the present work is not to originate the data or to pioneer the structure, merely to bring the two together for the UK case in a way that was novel (and remains novel at this level of granularity).

Resulting from that work, we were able to derive a measure of core and noncore liabilities in the UK regulated banking sector comparable to that of Errico *et al.* Their measure of noncore liabilities is defined from the bank balance sheet side, and includes deposits at ODCs that are outside broad money; debt securities issued by ODCs, MMFs, and OFCs; loans received by ODCs and OFCs; and nonresidents' deposits with ODCs and OFCs. For the UK, given our focus on safe assets from the perspective of the holder,

Figure 3.2: Time Path for Core and Non-core funding (UK regulated banks)



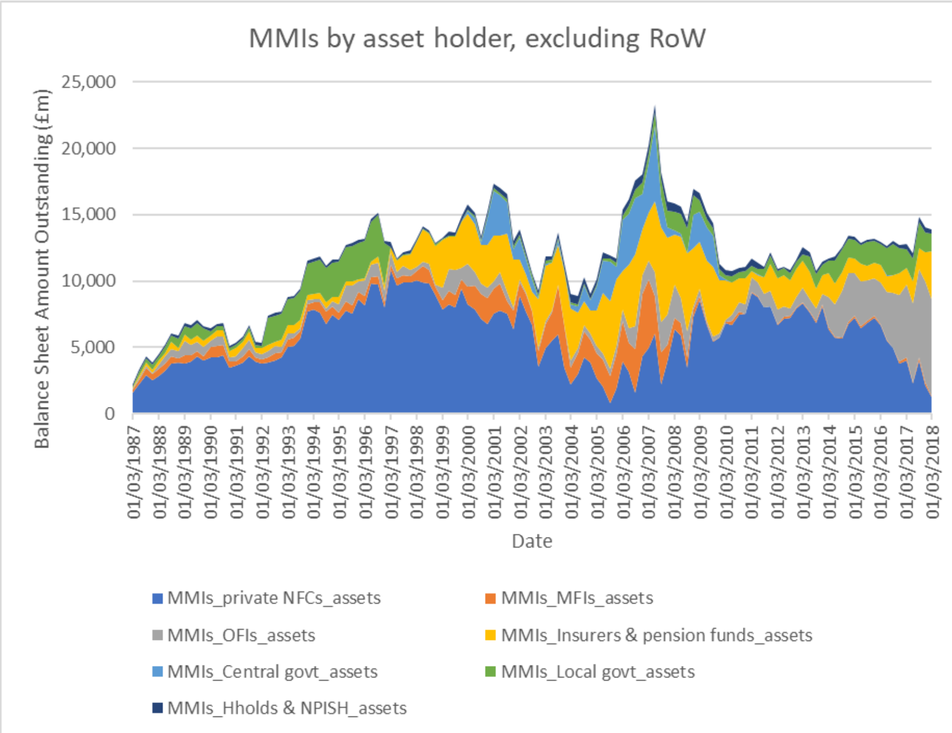
our measure is defined as total M4 (broad money) minus deposits with MFIs held by the household sector – it therefore includes sterling certificates of deposit; commercial paper, bonds, floating rate notes and other instruments of up to five years' maturity issued by UK MFIs; claims on UK MFIs arising from repos; and sterling bank bills. We therefore select M4 as the broad money measure from which we subtract household deposits to define our measure of noncore liabilities. Hereafter we refer to household deposits with UK-regulated banks as 'core', and the remainder of M4 as 'non-core'. This forms a very broad measure of shadow banking as any non-household funding source used by the financial sector in aggregate, but this is exactly the measure used in Errico *et al.* We depict in Figure 3.2 the time path of core (household deposits in M4) and noncore (rest of M4) funding for UK regulated banks.

Comparable to Figure 18 in Errico *et al*, Figure 3.2 depicts a rapid increase in noncore funding liabilities during the early 2000s boom, before sharp falls in nominal terms following the financial crisis of 2007/8. Recently noncore funding growth appears to have resumed – and as in Errico *et al*, core funding from retail depositors has proceeded largely unhindered. The variable noncore as defined here will be retained for further analysis.

From that broadest of definitions of shadow banking activity, we turn now to consider a much narrower one. Very little good data exists in most national aggregates to examine the potentially long chains of collateral rehypothecation entered into as part of the maturity, liquidity or credit enhancement functions of the shadow banking sector. Any effort to place the activities of the sector in macroeconomic context must therefore focus on one or other end of the chain. Previous authors, notably Bord & dos Santos [Bord and Santos, 2012], Purnanandam [Purnanandam, 2010] and Berndt & Gupta [Berndt and Gupta, 2009] have considered the role of shadow banking and the securitization machine in driving aggregate credit growth before the financial crisis, in doing so concealing risk and increasing fragility. Focusing in the present work on the provision of safe assets and the role of shadow banking in innovating in the money supply, we will consider the other end of the chain – the money market instruments where safety-seeking borrowers may warehouse cash against good collateral, further protected by net asset value guarantees. In particular we consider the short-term money market instruments issued by what the ONS defines as 'other UK residents' – to wit, not regulated banks, and therefore shadow banks in the truest sense of introducing into the financial system deposits seeking investment that may not otherwise be there.

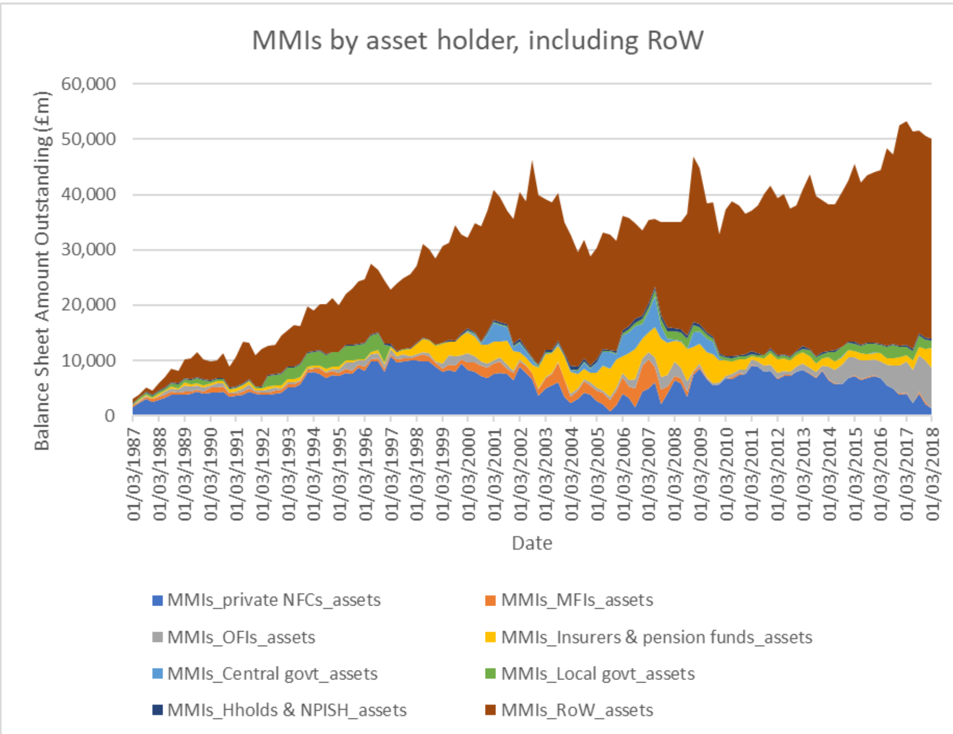
These money-market instruments are not large in aggregate – in contrast to Gorton *et al*'s [Gorton et al., 2012] estimate of 33% of GDP being composed of safe assets, money market instruments in the UK system of national accounts typically account for around 0.01% (1 basis point) of GDP, peaking at 1.5 bps in Q1 2001. There is significant interest in the composition of this money supply by asset-holder over time however. Excluding for the moment the rest of the world, Figure 3.3 depicts the time series of this composition at quarterly frequency, 1987:Q1 – 2018:Q1.

Figure 3.3: MMIs by Asset Holder, excluding RoW



We see the expected growth before the financial crisis followed by a decline in this funding source – though it is interesting to note the buying activity of private nonfinancial corporates during this time, perhaps rotating cash out of riskier uncollateralized positions with stressed commercial banks. Corporates began to sell down their positions in aggregate from 2011, though total volume remains approximately constant with the bid being taken up by OFIs, who constitute the majority of the domestic market as of mid-2017. Including the Rest of the World in Figure 3.4, observe that foreign asset holders are the majority of the market in aggregate, and recovered more quickly from the credit crunch as a shareholder class – perhaps also motivated by a flight-to-safety instinct or desire for greater liquidity.

Figure 3.4: MMIs by Asset Holder, including RoW



3.3.2 Conclusion

It is these money market instruments that will be a predominant focus in the rest of the work as we consider the relationships between the safe assets produced by the shadow banking sector, other safe assets, and the wider macroeconomy. To do so we assemble a time series dataset from publicly-available sources, at the quarterly frequency and stretching back to 1967 for some indicators – though 1987 is more typical and the dataset becomes acceptably dense after this point. We include measures of money market volume in addition to traditional money aggregates, macroeconomic variables, various interest rates, and alternative measures of financial conditions. The variables are detailed below, along with some abbreviations and notation used throughout the statistical results section of this work.

We will use various measures of shadow banking activity as dependent variables in the following empirical work, including the Errico-inspired measure of non-core financial sector funding ('noncore'), and also various components of the UK's balance sheet held in money market instruments (including but not limited to 'MMIs_OFIs_Liab'). We also construct a measure of securitisation activity by subtracting M4 lending excluding intermediate securitisation ('M4Lex') from the broader measure M4 lending ('M4L'), leaving just sterling value of securitisation activity. In adopting securitisation as a metric for shadow banking activity we follow authors such as Adrian & Shin, Pozsar *et al*, and Portes – all of whom have emphasised the role played by securitisation in shadow banking sector credit transformation [Adrian and Shin, 2009b, Pozsar et al., 2010, Portes, 2018].

3.4 Variable names and statistical notation

Table 3.4 gives the names, sources, and derivation of variables used in the empirical work hereafter. Some standard notation is also adopted, and summarised for convenience below.

Table 3.2: Variable names

Variable source code at data provider	Data provider	Variable name in statistical output in-text and Appendix A	Description of variable
	ONS (Office for National Statistics)	l_gdpdef	Natural logarithm of the GDP deflator (author calc)
		l_rgdp	log of real GDP (author calc)
	BoE	yrGilt1 / ytm10yrGilt	10-year gilt yield
	BoE	yrGilt / ytm20yrGilt	20-year gilt yield
	BoE	l_realM0	log of M0 notes and coins deflated by GDP deflator (log of real M0 notes & coins) (author calc)
	BoE	l_realM4	log of M4 deflated by GDP deflator (log of real M0 notes & coins) (author calc)
		l_yrGilt1 / l_ytm20yrGilt	log of 10-year gilt yield (author calc)
		L_yrGilt / l_ytm20yrGilt	Log of 20-year gilt yield (author calc)
	BoE	BankRate	Bank of England policy interest rate
	ONS	RPI	Annual % change in retail prices index
		TermSpread	Yield spread between policy rate and 10-year UK government gilt (author calc)
NYXK	ONS	MMI_Liab_total	UK aggregate balance sheet, total money market instruments issued as liabilities of UK non-bank FIs

NYXJ	ONS	MMIs_total economy_assets	UK aggregate balance sheet, total money market instruments held as assets of UK sectors and issued by UK nonbank FIs
NKZM	ONS	PNFC_MMI_Liab	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets of UK private nonfinancial corporates
NKEM	ONS	MMIs_public non-financial corporations_assets	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets of UK public nonfinancial corporates
NKKU	ONS	MMIs_private NFCs_assets	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets of UK private nonfinancial corporates
NNTS	ONS	MMIs_MFIs_assets	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets of UK regulated banks
NLQG	ONS	MMIs_OFIs_assets	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets of UK other financial institutions
NLTK	ONS	MMIs_OFIs_liabilities	Money market instruments issued by other UK residents (UK non-bank FIs) that are issued as liabilities of UK other financial institutions
NIYY	ONS	MMIs_Insurers & pension funds_assets	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets of UK insurers & pension funds

NSUO	ONS	MMIs_Central govt_assets	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets of UK central government
NJFG	ONS	MMIs_Local govt_assets	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets of UK local government
NNNK	ONS	MMIs_Hholds & NPISH_assets	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets of UK households & nonprofits
NLDQ	ONS	MMIs_RoW_assets	Money market instruments issued by other UK residents (UK non-bank FIs) that are held as assets by the rest of the world
LPQBC69	BoE	M4L	Aggregate M4 lending
RPQB57Q	BoE	M4Lex	Aggregate M4 lending excluding securitisation
		M4 securitisation	M4 lending minus M4 lending excluding securitisation (author calc)
		l_realM4_securit	Log of M4 securitisation, deflated by GDP deflator (author calc)
XUQABK67	BoE	EER	Quarterly average Effective exchange rate index - Sterling (Jan 2005 = 100)
LPQZ5GS	BoE	MFI_hding_InterOFC	Quarterly amounts outstanding of monetary financial institutions' sterling holdings of securities issued by Intermediate OFCs (in sterling millions) not seasonally adjusted

LPQBC56	BoE	MFI_lending_OFC	Quarterly amounts outstanding of monetary financial institutions' sterling net lending to other financial corporations (in sterling millions) seasonally adjusted
NYWQ	ONS	STDebt_CentGov	Balance Sheet, Total Economy, Short-term debt securities issued by UK central government
NYWY	ONS	STDebt_LocGov	Balance Sheet, Total Economy, Short-term debt securities issued by UK local government
NYXQ	ONS	LTDebt_CentGov	Balance Sheet, Total Economy, Long-term debt securities issued, by UK central government
NYXW	ONS	LTDebt_LocGov	Balance Sheet, Total Economy, Long-term debt securities issued, by UK local government
NKKC	ONS	PNFC_MFI_deposits	Private non-financial corporates' deposits with regulated banks
NKFB	ONS	PNFC_total_assets	Total financial assets of private non-financial corporates
NNMS	ONS	Hhold_MFI_deposits	Households' deposits with regulated banks
IUQAVNEA	BoE	LIBOR / LIBOR_1m	Quarterly average Sterling 1-month mean interbank lending rate
IUQAL1ESE	BoE	Euro_CPR_1m	Quarterly average of 1-month Euro-commercial paper rates:
IUQAVJND	BoE	Bill_DCR_1m	Quarterly average of eligible bills 1-month discount rate
IUQAGR1M	BoE	ON_gilt_repo	Quarterly average of overnight gilt repo interest rate

	Yahoo!	FTSE_Vol	Quarterly average FTSE100 volatility index (Yahoo Finance)

3.4.1 Notation

Prefixes

- **l_** - log of variable
- **lr_** - log of variable deflated by log of GDP deflator
- **d_** - first difference of variable
- **d_lr** - first difference of log of variable deflated by log of GDP deflator

Suffixes

- **_1** - 1-period lag
- **_2** - 2-period lag

Coefficient significance

- ******* = 0.01
- ****** = 0.05
- ***** = 0.1

Chapter 4

OLS and VECM Results

4.1 Replicating existing models of money demand

4.1.1 Introduction

Before investigating the hypotheses developed in Chapter 3, we first examine the behaviour of the traditional monetary aggregates in the quarterly dataset for comparison with the work of previous authors, and to calibrate methodology. We consider models of both narrow money – M0 notes & coins – and of broad money, M4 in the present study. In keeping with the practice in the literature, we estimate vector error correction models for both of these aggregates of interest – however we may derive some initial findings from a simple OLS specification relating these aggregates to measures of real economy activity, own and alternate interest rates, and inflation. Errico *et al* [Errico et al., 2014] also employ simple, OLS estimates to establish partial derivatives in their landmark work mapping the shadow banking system through a flow of funds methodology for the United States, and we follow their lead here. Though the nonstationarity present in some of these time series and the high R^2 values associated with the models typically indicate spurious regression, and though the Gauss-Markov conditions are typically not met in these models, Verbeek [Verbeek, 2008] demonstrates that in the presence of cointegration between the timeseries – of the form we go on to demonstrate here – the OLS estimator is 'superconsistent' for estimating the parameters of the long-run equilibrium relationship, and as such some limited inferences may be drawn. Exact model outputs are available in Appendix A, and are referred to in the text by the code under which they may be found in that appendix. Traditional monetary aggregate models belong to model Group A, and have codes of the form A1a, etc.

4.1.2 Methodology: the general vector error correction model

Developing the error-correction methodology of Sargan [Sargan, 1964] and the two-step, single-cointegrating-vector approach of Engle & Granger [Engle and Granger, 1987], the extension of error-correction time series models into higher-dimensional cointegrating space is due to Johansen [Johansen, 1988] and Johansen & Juselius [Johansen and Juselius, 1990]. The following section reproduces in large part the accessible discussion of the linear algebra of cointegration in the Gretl User Guide [Cottrell and Lucchetti, 2012]. Consider a simple vector autoregressive process of order p where y is a vector of length n, such as:

$$y_t = u_t + A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + e_t \tag{4.1}$$

As $y_{t-i} \equiv y_{t-1} - (\Delta y_{t-1} + \Delta y_{t-2} + ... + \Delta y_{t-i+1})$, which is to say that y is the sum of its past changes, we can cast the above in first difference form as:

$$\Delta y_t = u_t + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + e_t \tag{4.2}$$

This is known as the vector error correction form. Interpretation depends crucially on the rank r of the matrix Π, where if this matrix has rank greater than zero but less than the column span of the dataset n, cointegration exists. At the extremes:

- If $r = 0$, the processes are all integrated of order 1 and not cointegrated, and a VAR in first differences should be estimated.
- If $r = n$, the matrix Π is invertible, the processes are stationary, and cointegration analysis is not necessary.

- If $0 < r < n$, cointegration exists and Π can be decomposed as $\alpha\beta\prime$, where β holds the long-run cointegrating vectors and is $n \times r$, while α holds the parameters governing short-run response to disequilibrium and is $r \times n$.

The contribution of Johansen [Johansen, 1988] and Johansen & Juselius [Johansen and Juselius, 1990] was to provide a method to estimate the rank of the matrix Π by computing the eigenvalues of a closely-related matrix constructed to be symmetric and positive semidefinite, and therefore having positive real eigenvalues – the rank of this companion matrix is equal to the number of nonzero eigenvalues. Johansen [Johansen, 1988] derives critical values below which cutoffs the eigenvalues are not statistically distinguishable from zero. Because $\alpha\beta\prime = \alpha RR\beta\prime$ for some arbitrary conformable nonsingular matrix R, α and β are underidentified in the absence of identifying restrictions. In general for rank r, r^2 restrictions are needed to achieve identification. Normalising one coefficient per column to 1 (or -1 to cast that variable as the dependent) is an easy route to r such restrictions, and the other $r(r-1)$ can be drawn from economic theory or, as we do later, from statistical properties of the system variables. Overidentifying restrictions can also be tested by likelihood ratio in the pursuit of particular hypotheses motivated by theory. Otherwise, the long run relationships can be left underidentified at the cost of not being able to define standard errors or draw inferences regarding the long run equations – but without the loss of consistent numerical estimation. In the short-run equations, the Granger representation theorem holds that any set of nonstationary cointegrated variables can be characterized as being generated by an error correction mechanism – and indeed these variables are cointegrated only if this ECM exists. It is desirable that at least one equation in the system should respond to disequilibrium in each of the long-run relationships specified, and so should have a negative coefficient of statistical significance to the residuals of these relationships – moving the variable in the direction of 'closing the gap'.

It is these attributes – interpretable long-run and valid error-correction short-run equations – that we will look for in the empirical work directly following. Given our assumption that safe-asset substitutes suffer from inelastic supply in the short term, it is in the short-run equations that we will look for evidence towards our hypotheses H3 and H4 regarding demand substitution. Classical money-demand models are concerned with the long-run relationships of money quantities to GDP and inflation, so H1 and H2 will typically be assessed in light of the long-run parameter estimates.

4.1.3 Model group A

Guide to models: model group A

In group A we fit models to standard, not shadow-banking focused monetary aggregates with the aim of reproducing results similar to those found in the literature concerning money demand for the UK [Hendry and Ericsson, 1991, Drake and Chrystal, 1994, Nielsen, 2007]. Full details of all regressions are presented in Appendix A, and we summarise them here for ease of use. Models of group A1 concern the measure M0 notes and coins as dependent variable. Model A1a regresses log real M0 on log real gdp, the log of the gdp deflator, and the 20-year gilt yield. We find the expected positive significant coefficient to real GDP (0.23, $p<0.06$) and negative coefficient to the opportunity cost of holding money as measured by the yield on gilts (-0.03, $p<0.01$). However the large positive significant coefficient to the inflation measure violates the common assumption of price invariance in the literature, in this functional form (1.22, $p<0.01$). Model A1b substitutes the 10-year gilt yield for the 20-year, and the coefficient to real GDP now exceeds 1 (1.80, $p<0.01$) – however the relationship with inflation is now negative and significant (-0.88, $p<0.01$) and it may not be a coincidence that these sum to approximately 1, suggesting a 1-for-1 relationship between demand for narrow money and economic activity as expected in the literature. The coefficient to opportunity cost remains negative and significant (-0.04, $p<0.01$). Model A1c substitutes RPI for the GDP deflator as the measure of inflation, and the interpretation of the coefficients to real GDP ans outside interest rates are as A1a and A1b above – the coefficient to the inflation measure remains significant but is now small in absolute magnitude (0.01, $p<0.01$). These models are summarised in Table 4.1. Model A1d attempts to fit a VECM to the system composed of log real M0, log real gdp, RPI and the 10-year gilt yield, but as mentioned above this functional form does not elicit significant or satisfactory results. These results are nevertheless published in Appendix A herein.

Models of group A2 concern the broad money measure M4, in log real form deflated by the GDP deflator. Model A2a introduces log real gdp, the log gdp deflator, and the 20-year gilt yield as explanatory variables. Though the coefficient estimates are significant, the signs contradict our hypotheses and the published literature. Model A2b substitutes the 10-year gilt yield for the 20-year, but it does not enter the equation with a significant coefficient and other parameter estimates remain unsatisfactory. Model A2c substitutes RPI for log gdp deflator as the inflation metric, and returns more promising estimates. There is a positive coefficient to real gdp (1.95, $p<0.01$) and a negative relationship to gilt yields (-0.02, $p<0.05$), as expected. The RPI measure is small in magnitude but shows as significant (0.02, $p<0.01$) – this is typically expected to be zero. Subsequent models of group A2 introduce variables to act as proxies for broad money's own rate of return, and these might be expected to enter with positive sign if better compensation leads to larger real money balances being held. However negative relationships may be due to confounding supply effects making identification difficult – an asset of the holder is a liability of the seller, and higher interest rates may induce sellers to supply less money. Model A2d introduces LIBOR as a measure of return on money, and indeed we find the relationship to be negative, albeit small in magnitude (-0.02, $p<0.01$). Model A2e substitutes the Bank of England policy rate for LIBOR, still with M4 as the dependent, with similar results (-0.02, $p<0.01$). This is unsurprising given the close relationship between the policy rate and LIBOR. Model A2f dispenses with the 10-year yield but adds the difference between the 10-year yield and the Bank Rate as a measure we refer to as the Term Spread, and in this model both the Bank Rate and the Term Spread enter with positive sign. These results are summarised in Table 4.4.

System A2g estimates a VECM for the variables space composed of log real M4, log real gdp, RPI, the 10-year gilt yield, and the Bank of England policy rate, and is discussed below.

Table 4.1: Parameter estimates and significance for OLS models of group A1.

Variable	A1a	A1b	A1c
Log Real GDP	0.23*	1.80***	0.67***
Log GDP Deflator	1.22***	-0.88***	-
RPI	-	-	0.02***
10-year gilt yield	-	-0.04***	-
20-year gilt yield	-0.03***	-	-0.05***
R^2	0.97	0.92	0.88

A1: Models of M0 notes & coins

Group A1 concerns models of base or narrow money, defined here as the Bank of England's measure M0 notes & coins.

OLS Models The OLS forms summarised in Table 4.1 are not entirely without merit – in particular, all display the negative coefficient to gilt yields that would be expected, though it is small in magnitude. Other authors consider a risky rate of return such as commercial paper rates as the 'alternative' rate of return opportunity cost to holding money – by using long-dated gilt yields, our measure of opportunity cost embeds a term premium rather than a risk premium, casting money as sacrificing yield in exchange for immediacy – through the maturity transformation process of the banking sector. Otherwise, model A1b displays the expected sign and significance with respect to GDP and the level of prices – and it may be noteworthy that these coefficients sum to around unity, though all variables are in real terms. We stop short of implying a relationship between real money balances and nominal GDP. Both A1a and A1c have coefficients to real GDP of less than 1, and both also display a positive relationship to the incorporated measure of prices.

It should be noted also that the length of the 10-year and 20-year gilt yield series differs, with the 10-year yield providing more observations – as such it is generally preferred hereafter.

Table 4.2: Cointegrating vectors (unidentified) for system A2g

	Equation 1	Equation 2	Equation 3	Equation 4
Log real M4	-1	1.94	-50.63	2.14
Log real GDP	0.91	-1	177.14	-11.2
RPI	0.11	0.05	-1	-0.05
10-year gilt yield	-0.05	0.08	2.98	-1
Bank Rate	-0.06	0.06	2.37	0.44

A1d: VECM on M0 Despite an extensive specification search, we were unable to elicit a vector error correction form with desirable attributes for M0 notes and coins. We report an illustrative example as model A1d in the technical output appendix, but we do not discuss the results at length here. The Johansen procedure indicates a relatively large cointegration space of 3 cointegrating vectors for the 4-variable system, and so the long-run forms are underidentified, though the long run coefficient of real GDP to M0 money supply, at 0.57, is appropriate. The short-run equations lack desirable equilibrium-correcting properties, and following the work of [Jawadi and Sousa, 2013], it seems likely that nonlinear or time-varying parameters are at play here.

A2: Models of M4

Group A2 concerns models of broad money, defined here as the Bank of England's measure M4.

A2g: VECM of M4 Parameter estimates for system A2g are reported in Tables 4.2 and 4.3. Table 4.2 contains the long-run equations, and Table 4.3 contains the short-run parameter estimates.

Discussion: model group A

The longer time series permitted by use of the 10-year gilt yield in preference to the 10-year rate once again delivers estimates more in line with theory when M4 is the dependent variable – and as such we refrain from discussing model A2a at length. All other OLS models of M4 display positive and

Table 4.3: Short-run adjustment parameters for system A2g

Variable	Coefficient	P-value
d_lr_M4_1	0.09	0.29
d_lr_gdp_1	-0.55	0.02**
d_RPI_1	0.01	0.001***
d_ytm10yrgilt_1	0	0.97
d_bankrate_1	0	0.66
EC1	-0.01	0.17
EC2	-0.01	0.000***
EC3	0.0005	0.000***
EC4	0.0002	0.9
R^2	0.3	

Table 4.4: Parameter estimates and significance for OLS models of group A2

Variable	A2a	A2b	A2c	A2d	A2e	A2f
Log Real GDP	-0.92***	1.44***	1.95***	1.67***	1.67***	1.67***
Log GDP Deflator	3.74***	0.71***	-	0.62***	0.61***	0.61***
RPI	-	-	0.02***	-	-	-
10-year gilt yield	-	0.003	-0.03*	0.03*	0.04***	-
20-year gilt yield	0.12***	-	-	-	-	-
LIBOR	-	-	-	-0.02***	-	-
Bank Base Rate	-	-	-	-	-0.02***	0.02*
Term Spread	-	-	-	-	-	0.04***
R^2	0.96	0.92	0.88	0.97	0.97	0.97

significant wealth effects, with coefficients to GDP ranging from +1.44 to +1.95. As with some of the M0 models, coefficients concerning levels or changes in price tend to be positive. A2c, including RPI as an explanatory variable, defines a hyperplane solution that is decreasing in increasing gilt yields, as would be expected from an alternative, opportunity-cost interest rate. Other models however estimate a positive coefficient to gilt rates. This may be due to the composition of M4 – as this aggregate includes lending activity by regulated banks, lending activity may be increasing in increasing gilt rates as the net interest margin of the lending bank may be higher. As such, including the 10-year gilt rate in this regression may be proxying term premia, which we would expect to be positively correlated with at least the lending component of M4. Models A2d and A2e include short-term interest rates – LIBOR and the Bank of England Base Rate respectively – and both these rates enter the equation with negative sign. This also may be attributable to the effect of short rates on net interest margin – as banks borrow short and lend long, all other things being equal, increasing long rates (or equivalently term premia) increase the net interest margin and incentivise lending, while increasing short rates lower the margin [Genay, 2014].

Applying the Johansen procedure to the system (log real M4, log real GDP, RPI, 10-year gilt yield, Bank Rate) suggests that, while the smallest eigenvalue is indistinguishable from zero and cointegration therefore exists, four vectors are required to span the cointegrating space of this five-variable system, and identification of the long-run equations on purely theoretical grounds is extremely difficult. Some novel identification strategies are presented later within the present work, but are outside the scope of this replication-focused analysis of standard monetary aggregates. As such, we define the cointegrating vectors up to a normalisation only, and otherwise leave them unconstrained. The cointegrating vector normalised on log real M4 has a positive coefficient to log real GDP of +0.91, though it is not possible to say if this is significant. RPI also enters the long-run equation for M4 with positive sign, while the partial derivatives with respect to both policy rates and 10-year gilt rates are negative. In the short run, changes in log real M4 money supply do not display a significant autoregressive component, but do respond negatively to positive changes in log real GDP. Money supply also is not found to respond significantly to disequilibrium in the long-run equation for which it is cast as the dependent – log real M4 instead corrects disequilibrium in long-run equation 2, cast as the long-run equation for GDP.

To briefly summarise and compare with existing money supply literature focused on the UK – coefficients are estimated with the expected sign more often than not, notwithstanding some superficially unusual but logically explicable responses to term premia in the case of M4. We find that M0 responds to real GDP with a magnitude typically <1, and less than that estimated for M4, which is typically 1.7. This approximates the results of McNown & Wallace [McNown and Wallace, 1992], who find coefficients typically <1 for narrow money and >1 for broad money. Magnitudes of parameter estimates for own and alternate rates of return are somewhat different to the magnitudes published in existing literature, being typically much smaller – though this may be a result of differing variable encoding between the present study and antecedent literature. We report parameter estimates around 0.02 to 0.1, whereas 6 to 7 is estimated in, for example, Ericsson *et al* [Ericsson et al., 1998]. Having replicated existing models of money demand using standard dependent variables with some success, we now turn our attention to the shadow banking sector to see if similar specifications can be elicited for measures of activity in that sector.

4.2 The shadow banking sector and the provision of safe, money-like assets

4.2.1 Introduction

We first considered multiple individual variables that address or proxy some element of shadow banking activity in addressing the hypotheses outlined in Table 3.1. In the regressions outlined below these range from a relatively narrow measure, log real amounts outstanding of Money Market Instruments issued by Other Financial Intermediaries, through the broader categories of (log real) all MMI assets held by UK sectoral counterparties and a constructed measure we term ‘M4 securitisation’, to the broadest measure of all – a measure of ‘noncore’ banking sector liabilities defined after Errico *et al* [Errico et al., 2014] and constructed as outlined in Chapter 3 above.

4.2.2 Guide to models: model group B

Models of group B concern measures of shadow banking sector activity, defined as aggregate quantities of financial instruments outstanding, at varying levels of specificity. Group B1 models take the narrowest measure, money market instruments (MMIs) issued by other financial intermediaries (OFIs), as the dependent variable - referred to as ‘logreal_B1’. Model B1a regresses this measure on log real gdp, RPI, and the 10-year gilt yield. The positive, significant coefficient to real GDP (1.20, $p<0.01$) is in line with the hypothesis that shadow banking narrow money provision scales with real economic activity in a similar way to demand for central bank narrow money. Model B1b includes a measure of M4 broad money which enters with negative sign and significance (-0.76, $p<0.01$). Model B1c introduces M0, the measure of official central bank narrow money, and this enters the system with negative sign, large magnitude and significance (-3.09, $p<0.01$) – as one would expect if shadow bank and central bank money are treated as substitutes. The absolute magnitude (>1) of this estimate also suggests a procyclical attribute to shadow bank narrow money creation – ‘overreacting’ to injections or withdrawals of official money. Model B1d introduces the overnight gilt repo rate as a measure of the return on shadow bank narrow money, and this enters with expected positive sign and marginal significance (0.02, $p=0.07$). Removing the insignificant independent variables from model B1d yields model B1e, an appealing specification showing quantity of shadow bank narrow money responds positively to real economic activity (0.63, $p<0.01$) and to own interest rate (0.03, $p<0.01$), and negatively to broad money quantity (-0.23, $p<0.01$) and to inflation, a measure of the opportunity cost of holding nominal money balances (-0.02, $p<0.01$). These regressions are summarised in Table 4.6.

Model B1f fits a VECM to the system composed of log real money market instruments issued by OFIs, log real gdp, log real M4, RPI, and the overnight gilt repo rate. The long run relationships are left unidentified in the absence of plausible identifying restrictions, but are normalised to the shadow bank money measure, real gdp, and real M4 for interpretability. The short-run estimates indicate that shadow bank money responds to disequilibrium in the long-run equation for real GDP ($\lambda = -0.33$), and also displays a significant negative relationship to one lag of M4 quantity (-0.99, $p<0.01$) – suggesting that an increase (decrease) in broad money leads to an almost precisely offsetting fall (rise) in shadow bank issued money market instruments the following quarter.

Models of group B2 concern the constructed measure of M4 securitisation as the dependent variable. B2a offers an OLS equation comprising log real gdp, log real M4, RPI and the overnight gilt repo rate as explanatory variables. Only the measures of internal return and opportunity cost – the repo rate and RPI respectively – display the expected sign and significance. Model B2b fits a VECM to the same system of variables involved in B2a, but a tractable system of short-run equations proves elusive.

Models of group B3 extend the measure of shadow bank money to all money market instruments issued by UK residents, a sector sum we transform into log real terms and refer to as 'l_realB3'. The contemporaneous OLS model B3a incorporates log real gdp, RPI, the 10-year gilt yield as external return, and the overnight repo rate as a measure of the return to holding shadow bank money. All variables except real gdp (which is insignificant) enter with the expected sign and significance. Model B3b fits a VECM to the same variable space, and the long-run forms reported in Table 4.7 show promise. In the long-run equation with shadow bank activity as the dependent variable, equilibrium relationships are as hypothesised – positive to GDP (4.76), negative to M4 (-1.40), positive to the overnight repo rate (0.21) and negative to the yield on gilts (-0.09). The short-run forms prove intractable once more, but are reported in Table 4.8 nevertheless.

Models of group B4 are all vector error-correction models, and introduce measures of alternative safe asset issuance by banks and government in order to address hypotheses H3 and H4. Model B4a estimates a system composed of log real M4 securitisation, log real gdp, log of the gdp deflator, 1-month LIBOR, the 20-year gilt yield, and log real short-term central government debt outstanding. The Johansen rank-selection procedure suggests one or two long-run equations, and we estimate and report both. Model B4a presents the single long-run equation form, and we normalise to the measure of shadow banking activity as the 'dependent' of this long-run equation. We find the expected negative equilibrium relationship with government debt issuance (-1.33), positive relationship with GDP (42.57) and negative relationship with inflation (-18.43), but the return metrics confound expectations. The short-run equations suggest that shadow banking activity does correct disequilibrium in the long-run relationship ($\lambda = -0.04$). Model B4b introduces the 2-equation long-run forms, and the long-run form with shadow banking activity as the dependent has similar properties to B4a, as does the short-run equation with shadow banking activity as the dependent.

B4c and B4d mirror B4a and B4b respectively but substitute the measure of long-term debt issuance by central government for the short-term measure. Neither produces a short- or long-run system that provides evidence for our hypotheses, and we do not discuss them in detail here.

Model B4e introduces a (log real) measure of deposits held in the traditional banking sector by private non-financial corporates ('lr_PNFC_MMI_deposits'). We thereby seek to address our hypothesis H3, that corporate cash pools are a key source of demand for shadow banking sector safe assets. Log real M4 securitisation remains the proxy for shadow banking activity. The long-run equation with shadow banking activity as the dependent displays the expected negative relationship in equilibrium with regulated bank deposits (-1.41) – however this estimate is not significant given the identifying restrictions used.

Model B4f introduces quarterly realised volatility in the FTSE 100 as an exogenous explanatory variable in the short-tun adjustment equations. This volatility measure aims to proxy financial distress, and the coefficient should capture how financial stress impacts demand for shadow banking sector services. Initially we permit this measure to enter contemporaneously, and the coefficient in the short-run equation for log real M4 securitisation is positive and significant (0.002, $p<0.05$), suggesting that elevated financial distress increases securitisation activity at the margin – possibly as regulated banks, faced with volatility in their equity holdings and loan securities, seek to move assets off-balance-sheet. However this may also reflect a preference by safe-asset demanders for instruments that are explicitly asset-backed, or are at arms' length from troubled publicly-traded banks. Model B4g modifies the FTSE volatility variable to enter the short-run equations with a one-quarter lag. Model B4g is our preferred functional form, and is therefore discussed in more detail hereinafter.

Model B4h fits a VECM system around the broadest measure of shadow banking activity, non-core bank funding as defined by Errico *et al* [Errico et al., 2014]. It does not yield evidence in support of our hypotheses and is not discussed in detail here, though full parameter estimates are published in Appendix A, as they are for all other models estimated.

4.2.3 Summary of results: model group B

Contemporaneous OLS models concerning MMIs liabilities issued by OFIs display the expected sign and significance with respect to GDP, coefficients varying from 0.63 to 4.65 depending upon specification. RPI as a measure of opportunity cost also enters with the expected (negative) sign and is significant though of smaller magnitude. Alternative measures of narrow and broad money, introduced as controls, also pick up some significance in these specifications. Among the vector models, the preferred model for this most limited of SBS measures, model B1f, estimates a negative coefficient to GDP in the long-run equation – albeit with the caveat that the long-run relationships in this case are under-identified, and so significance cannot be assessed. A tractable short-run error correcting relationship for this system proved elusive.

Modelling the constructed measure M4 securitisation as a proxy for activity in the shadow banking sector yields the vector systems B2b and B4g, where B4g also includes measures of long-term central government debt issuance and private non-financial corporates' holdings of deposits in the regulated banking sector in order to address hypotheses H3 and H4 as defined above. In both cases the measure of interest is in log-real terms, and as such the long run relationship with the measure of price level is constrained to be zero to achieve identification and estimate standard errors for the long-run equations. B4g yields the form that most closely complies with the hypotheses – albeit with a large and marginally-significant coefficient of 39.29 to log real GDP. Measures of long-term central government debt issuance and PNFC deposits in regulated banks do not enter the long-run cointegrating relationships with significance, and so no evidence can be given for hypotheses H3 and H4 from this part of the model. However, the short-run adjustment equation corresponding to this long-run form and with (the first difference of) log real M4 securitisation as the dependent contains a negative and significant coefficient of -1.14 to long-term debt issuance by the central government, and this may be considered as evidence in favour of the 'crowding out' hypothesis due to Krishnamurthy & Vissing-Jorgensen [Krishnamurthy and Vissing-Jorgensen, 2012]. The short-run equation for (change in log real) M4 securitisation is as follows:

$$\begin{aligned}\Delta lr\_M4\_sec = &- 14.13 + -0.18 * \Delta lr\_M4\_sec_{t-1} + 0.98 * \Delta l\_gdpdef_{t-1} \\ &+ 0.09 * \Delta LIBOR\_1m_{t-1} + -0.08 * \Delta ytm\_20yrGilt_{t-1} \\ &+ -1.14 * \Delta lr\_LT\_Debt\_CG_{t-1} + 0.70 * \Delta lr\_PNFC\_MFI\_deposits_{t-1} \\ &+ 0.001 * FTSE\_Vol_{t-1} + 0.03 * \lambda_1 + -0.47 * \lambda_2\end{aligned} \tag{4.3}$$

where all variables are named as in the statistical tables with the exception of λ_1 and λ_2, which give the error-correction speed-of-adjustment parameters with respect to the first (λ_1) and second (λ_2) long-run equations. The first long-run equation is normalised to the measure of securitisation activity and is reported in Table 4.7 , while the second equation is normalised to the gdp deflator and is reported in Appendix A.

4.2.4 Discussion: model group B

Applying the time-series methodology of Johansen [Johansen, 1988] to the question of shadow banking as a provider of monetary services, we document evidence from the short-run model in favour of our hypothesis H4. Equation 4.3 shows the short-run equation with M4 securitisation as the dependent variable, and the significant coefficient of -1.14 to central government debt

Table 4.5: Hypotheses, revisited

Hypothesis	Variable entering SBS money demand function	Expected sign and magnitude	Evidence from VECM models
H2	Log real GDP	+ , approximately 1	B3b and B4g positive but of much greater magnitude
H2	Own interest rate	+	B4g positive to LIBOR in long-run form
H2	Opportunity cost / alternative interest rates	–	Inconclusive – N4g positive to term rates in long run, negative in short run
H3	Corporate deposits in traditional banking sector	– , around 1 in absolute magnitude if 'crowding out' is total	Inconclusive
H4	Government debt outstanding, government debt issuance in short-run models	– , as above 1 in absolute magnitude if crowding out is total	Good – B4g shows significant short run response to change in level of outstanding central government debt (ie. issuance), and close to hypothesized magnitude

Table 4.6: Contemporaneous OLS results for models of group B1

Model Code	B1a	B1b	B1c	B1d	B1e	B2a	B3a
Dependent Var	log real MMIs OFIs liabilities	log real MMIs OFIs liabilities	log real MMIs OFIs liabilities	log real MMIs OFIs liabilities	log real MMIs OFIs liabilities	log real M4 securitization	log real MMIs excluding RoW
log real GDP	1.21***	2.64***	4.65***	0.98*	0.63***	-1.93***	-0.37
RPI	-0.09***	-0.07***	-0.04***	-0.02***	-0.02***	-0.03**	-0.02**
10-year gilt yield	0.01	-0.004	-0.09***	0.004	-	-	-0.06***
Overnight gilt repo rate	-	-	-	0.02*	0.03***	0.04***	0.02*
log real M4	-	-0.76***	0.06	-0.23***	-0.23***	4.34***	-
log real M0 notes & coins	-	-	-3.09***	-0.22	-	-	-
$R2$	0.57	0.61	0.87	0.73	0.73	0.99	0.16

Table 4.7: VECM long-run equations for systems of group B

Model Code	B1f	B2b	B3b	B4g
Dependent Var	log real MMIs OFIs liabilities	log real M4 securitisation	log real MMIs liabilities excl RoW	log real M4 securitisation
log real GDP	-5.2	-7.88***	4.76***	39.29*
RPI	-0.81	0.00 (constrained)	0.00 (constrained)	-
log GDP deflator	-	-	-	0.00 (constrained)
10-year gilt yield	-	-	-0.09	-
20-year gilt yield	-	-	-	3.21***
Overnight gilt repo rate	0.51	-0.32***	0.21***	-
1-month LIBOR	-	-	-	0.02
log real M4	4.52	4.66***	-1.40*	-
log real M0 notes & coins	-	-	-	-
log real long-term central govt debt	-	-	-	1.85
log real private non-financial corporates deposits with MFIs	-	-	-	-5.9

Table 4.8: VECM short-run equations for variables of interest in systems of group B

Model Code	B1f	B2b	B3b	B4g
Dependent Var	log real MMIs OFIs liabilities	log real M4 securitisation	log real MMIs liabilities excl RoW	log real M4 securitisation
autoregressive term in diffs	0.14	-0.07	-0.16	-0.18
diff log real GDP t-1	0.82	-2.28	-3.02*	-5.36***
diff RPI t-1	0.01	0.01	0.04**	-
diff log GDP deflator t-1	-	-	-	0.98
diff 10-year gilt yield t-1	-	-	0.002	-
diff 20-year gilt yield t-1	-	-	-	-0.08*
diff overnight gilt repo rate t-1	-0.03*	-0.004	-0.04	-
diff 1m LIBOR t-1	-	-	-	0.09***
diff log real M4 t-1	-0.99***	-0.76	-0.62	-
diff log real M0 notes & coins t-1	-	-	-	-
diff log real long-term central govt debt	-	-	-	-1.14***
diff log real PNFC deposits at MFIs	-	-	-	0.70*
Acceptable error correction specification?	No - LR eq 1 has no correction mechanism	No - LR eq 1 has no correction mechanism	No - no significant responses to disequilibrium	Yes - correction to diseq flows through rates - LIBOR and gilt yields

issuance implies that extra availability of government debt drains deposits out of the shadow banking system, and correspondingly a fall in government debt issuance leads to increasing securitisation and shadow bank money issuance the following quarter. With a standard error of 0.34 the coefficient is statistically distinguishable from zero with $p < 0.01$, but it is not statistically distinguishable from 1 and we may tentatively conclude that 'crowding out' of the shadow banking sector by government-issued safe assets is supported in the data. This finding accords with the work of Krishnamurthy & Vissing-Jorgensen [Krishnamurthy and Vissing-Jorgensen, 2012] and supports the assertion of Pozsar [Pozsar, 2013] and of Gorton *et al* [Gorton et al., 2012] that the shadow banking sector arises in response to insufficient quantities of government debt for purchase as safe assets. We assume that quarter-to-quarter issuance of government debt is related to government's need for working capital and not the demand for quality collateral within the financial sector, and on that basis we identify shifts in shadow banking activity with shifts in demand for shadow banking services, rather than idiosyncratic shifts in supply.

Though we demonstrate evidence for hypothesis H4 regarding substitutability of shadow banking assets with government debt, support for our other hypotheses remains weak – and a potential culprit is that our chosen dependent variables are poor proxies for shadow banking activity, or fail to incorporate enough information. In the next chapter we take inspiration from Stock & Watson, Bernanke *et al*, and Banerjee & Marcellino to derive information from considering a broader set of potential dependent variables [Stock and Watson, 2002, Bernanke et al., 2005, Banerjee and Marcellino, 2009].

Chapter 5

The Shadow Banking Factor

5.1 Principal Components Analysis

5.1.1 Introduction

With only weak evidence for the hypotheses arising from specific, individual-variable-focused regression forms in the previous chapter, we now consider methods whereby the larger column span of our money-market-funds-by-investor dataset may be leveraged to provide extra information.

Dimension reduction strategies for data analysis, and more generally techniques for uncovering latent 'fundamental' structure in datasets, are commonplace in the social and hard sciences. Psychologists, biologists and others who deal chiefly with cross-sectional data with many attributes but perhaps relatively few rows ('large p small n') were early adopters of the methods of principal components and exploratory factor analysis. The literature concerning their use in economics is due in large part to the prolific statisticians and longtime co-authors James Stock and Mark Watson. Though pioneered by Sargent & Sims in 1977's 'Business cycle modelling without pretending to have too much *a priori* economic theory' [Sargent et al., 1977], factor strategies owe much of their prominence in econometrics to the work of Stock & Watson, beginning with 1998's 'Diffusion Indexes' [Stock and Watson, 1998]. The present work is closest in spirit to Stock & Watson's 2002 'Forecasting using principal components from a large number of predictors' [Stock and Watson, 2002]. Therein, it is established that a correlated time series dataset can be summarized by a potentially smaller number of uncorrelated, unobservable factors – and that these factors can be consistently recovered (in the statistical sense) by the method of principal components under fairly general assumptions about what form the cross-sectional and temporal correlations within the original dataset take. Treating these principal components as estimates of the unobservable factors, Stock & Watson are then able to incorporate them in otherwise standard forecasting VARs.

Bernanke *et al* [Bernanke et al., 2005] employ a similar approach to pioneer the factor-augmented vector autoregression (FAVAR). They also estimate the latent factors by the method of principal components, also offering a Bayesian likelihood approach which we do not pursue here. FAVARs have since become commonplace in the literature, but the present work may be subcategorized as the relatively rarer factor-augmented vector error-correction model (FAVECM), introduced by Banerjee & Marcellino [Banerjee and Marcellino, 2009]. Banerjee & Marcellino characterize the functional form – and we agree – as a natural extension of the FAVAR, and further note that just as standard VARs in first differences may be misspecified (or at least improved upon) in the presence of cointegration, so too must be factor-augmented VARs. Banerjee & Marcellino consider as their examples US interest rates and the US macroeconomy generally, and the present work is believed to be a novel application of the FAVECM to the field of shadow banking – and possibly to the broader field of money demand. A further point of differentiation is that Banerjee & Marcellino introduce factor representations to augment the study of 'real' (non-constructed) macroeconomic variables, whereas in the present study the factors themselves are the object of focus.

An assumption of the methodology is that one or more latent (unobservable) factors exists, and captures the phenomenon of interest – in this case we assume the existence of two latent factors carrying information about the level of shadow banking activity, and we further assume that measured variables contain information about and are correlated with these latent factors, but no one observable variable is equal to a latent factor. Owing to the normalisation of the data that takes place during the principal components procedure, the ability to interpret the coefficients of the FAVECM as semi-elasticities or elasticities is lost – the factors are in z-score terms. We can still make statements about sign and significance, and perhaps about the behaviour of explanatory variables when the latent factors are above or below their own mean.

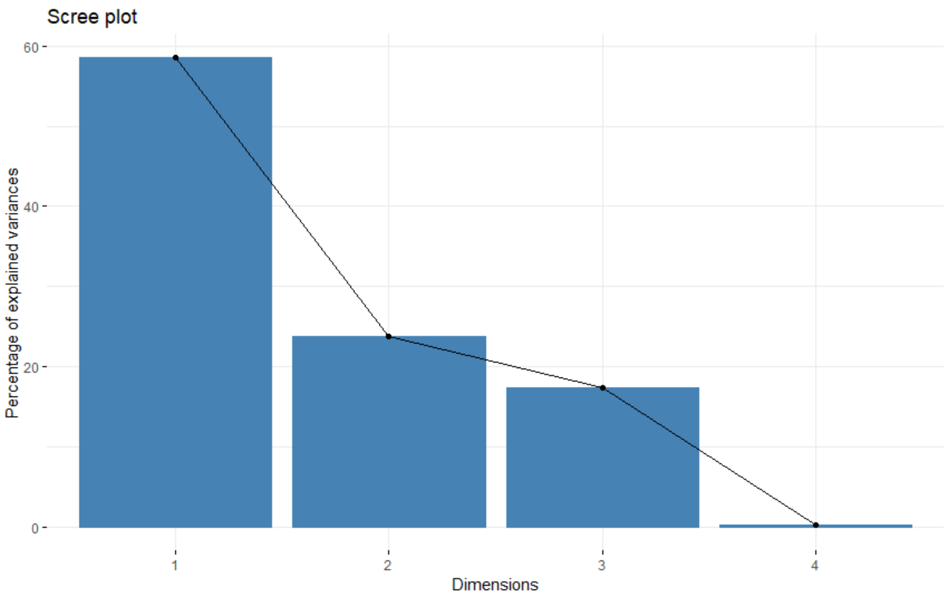
5.1.2 Results

We consider four possible structures for a factor structure study of the shadow banking activity dataspace:

- Panel 1a: A small, four-column dataset containing the Errico 'noncore' measure, our constructed measure M4 securitisation, and total MMI asset and liability series, with all variables entering in log real terms;
- Panel 1b: The same four variables in first-differenced log real form;
- Panel 2a: An expanded dataset with the four previous variables, in addition to measures of MMI holdings broken out by economic sector: PNFCs, MFIs, OFI assets, OFI liabilities, Insurers & Pension Funds, local government, households, and the Rest of World sector. As before all variables are in log-real terms;
- Panel 2b: The first-differenced version of the above.

Panel 1a Panel 1a: After normalising and scaling the input variables to be mean zero and have unit variance, we extract the principal components. In general, and unlike the rank-reduction cointegration work of Johansen relied upon above, the principal components of a dataset may span a space of dimension equal to the dataset, that is to say there are as many principal components defined as there are variables in the dataset. However, like the Johansen procedure [Johansen, 1988], principal components are closely related to the eigenvalues of (the covariance matrix of) the dataset, and so some 'later' principal components may be discarded as they explain little of the remaining unspanned variance in the dataset. The proportion of variance spanned by each successive principal component may be assessed numerically, where a rule of thumb is to seek at least 50% explained variance,

Figure 5.1: Scree plot of variance structure in Panel 1a

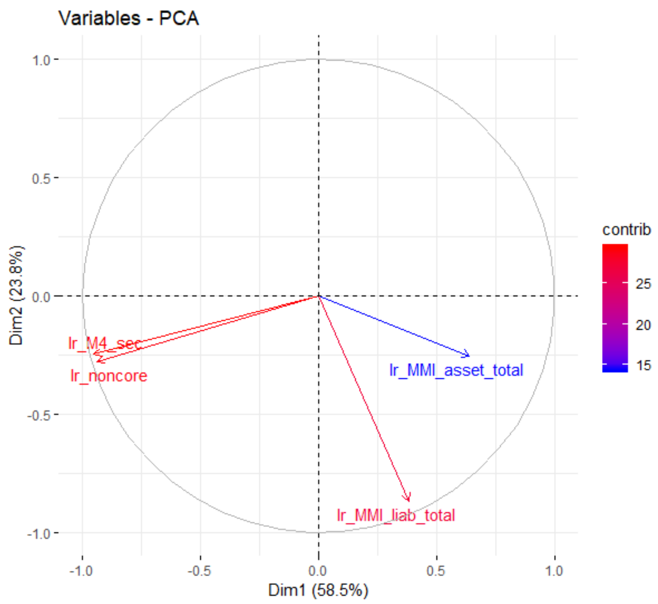


or visualised in a scree plot like Figure 5.1 below. In analysing a scree plot it is practice to look for an 'elbow' where the next principal component adds substantially less explanatory power than the component that preceded it.

In the case of panel 1a, this 'elbow' is notable at principal component 2, and the first component accounts for nearly 60% of the variance in the dataset. Following the Stock & Watson procedure [Stock and Watson, 2002], it would be acceptable to incorporate just the first principal component of panel 1a into a subsequent analysis.

We can also graph the variable loadings on the first two principal components to gain more information about the covariance structure of the dataset. Figure 5.2 below depicts this plot for panel 1a – and we can see that the first principal component contains information about the variables noncore and M4 securitisation, while the measure of MMI assets, and particularly liabilities, load on principal component 2.

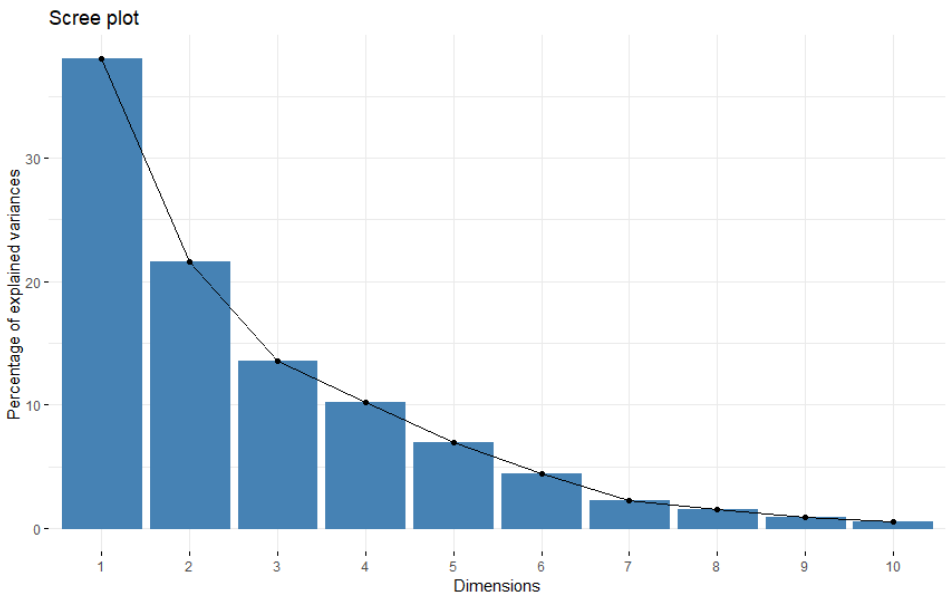
Figure 5.2: Variable loading on Principal Components 1 and 2 of Panel 1a



Panel 2a A similar analysis was carried out for the other 3 panels, and full results are shown in Appendix B. Panel 2a, the larger panel of undifferenced variables, offered the most promising results and the analysis hereinafter will focus upon that dataset exclusively. Figure 5.3 below depicts the scree plot of explained variance associated with the principal components of panel 2a, and Figure 5.4 depicts the variable loadings.

As with panel 1a it will be seen that principal component 1 contains information about the variables noncore and M4 securitisation, now joined by MMIs held by local governments. These variables are somewhat negatively correlated with total MMI assets, which loads negatively on PC1 along with MMI liabilities to OFIs, and MFIs MMI assets. Broadly uncorrelated with the above, by orthogonality of principal components, are MMI assets held by the Rest of the World, PNFCs, and the measure of total MMI liabilities in the UK economy. Indeed this finding is borne out by examining X-Y scatterplots of the variables themselves, an example of which (M4 securitisation vs. Rest of World MMI assets in the UK) is shown in Figure 5.5 below.

Figure 5.3: Scree plot of variance structure in Panel 2a

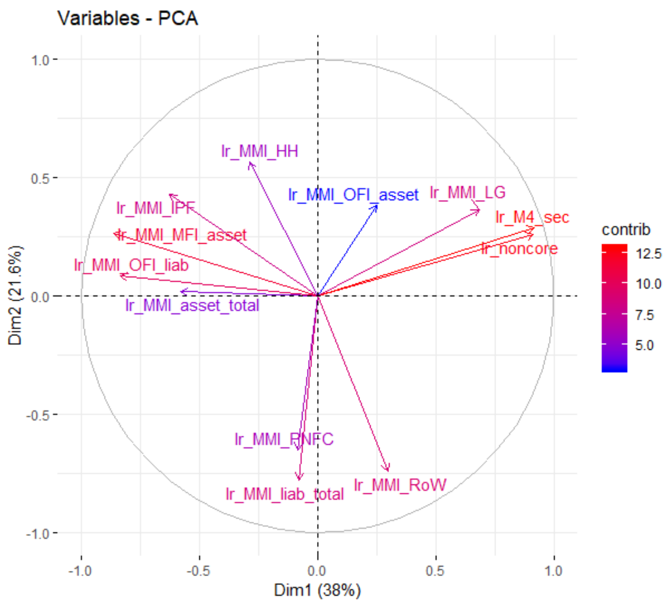


Given the 59% of variance explained by the first two principal components, along with their identifiability with underlying transactional phenomena, these will form the factors to be incorporated into subsequent analysis. Hereafter, we term Panel 2a's first principal component 'SBS Factor 1' and the second component 'SBS Factor 2'.

5.2 Factor-Augmented VECM

Having derived by principal components analysis, estimates of the latent factors driving activity in the ultimate liabilities of the shadow banking sector, we now incorporate these estimated factors into vector systems to assess their validity with respect to our hypotheses about shadow banking behaviour. The system we attempt to solve also includes log of real GDP, log of the GDP deflator as a measure of price level, 1 month LIBOR and the 20-year gilt yield (both of which enter untransformed), PNFC deposits with regulated banks, and central government long-term debt outstanding. We

Figure 5.4: Variable loading on Principal Components 1 and 2 of Panel 2a



also permit a measure of the realised volatility of the FTSE 100 (proxying times of financial turbulence) to enter the short-run adjustment equations, though we do not postulate its membership of a long-run equilibrium system.

The Johansen method for assessing the number of cointegrating relationships offers some evidence for either 1 or 2 such equations, and as such we assess both. In the 2-equation model, we employ what is believed to be a novel identification strategy in this field. As the SBS factors were estimated by the method of principal components, they are orthogonal by construction, and so each factor can be constrained to have coefficient zero in the long-run equation normalised to the other – without loss of information as these variables are known to be uncorrelated.

5.2.1 Guide to models: group C

Incorporating the shadow banking factors into a VECM specification, we report the single-long-run-equation form as model C1a. Table 5.1 contains the parameter estimates of this long-run equation, normalised to SBS Fac-

Figure 5.5: Scatterplot of log real MMIs held as assets by Rest of World sectors (x-axis) and log real M4 securitisation (y-axis)

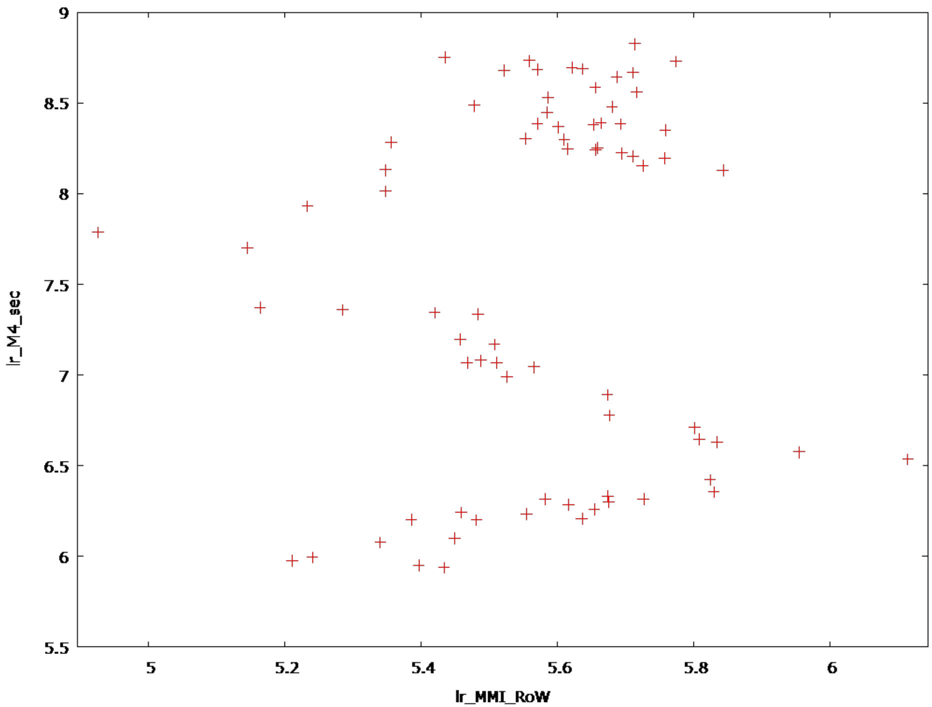


Table 5.1: Model C1a: cointegrating vector

Cointegrating Vector	Coefficient	Standard Error
SBS Factor 1	-1	0
SBS Factor 2	1.21	0.46
log GDP deflator	125.58	40.78
log real GDP	-119.64	34.28
LIBOR 1m	-2.35	0.49
20-year gilt yield	-5.84	1.37
log real PNFC deposits	20.58	12.17
log real long term central government debt	-28.3	5.98

tor 1. Table 5.2 contains the short-run equations with SBS Factor 1 and SBS Factor 2 as the dependent variables, the other short-run equations are reported in Appendix B.

We present the results of the two-long-run-equation form as model C1b. Table 5.3 contains these cointegrating vectors, normalised to SBS Factors 1 and 2. Table 5.4 contains the short-run equations with SBS Factors 1 and 2, and long-term government debt issuance, as dependents, and the other short-run adjustment equations are presented in Appendix B.

5.2.2 Discussion

While the single long-run equation is trivially identified by a normalisation on SBS Factor 1, its coefficients defy easy interpretation and its associated error correction model is not admissible as no error correction takes place at a significant level of correct sign. Furthermore, both SBS factors appear exogenous in the short-run equations, with no significant coefficients appearing at any level.

The 2-equation FAVECM offers more promising results. The identification strategy employed allows the standard hypotheses to be assessed for both of the factor measures of SBS activity. Both display the expected negative sign to price level and positive coefficient to GDP, with the coefficient magnitudes likely inflated by the normalising procedure carried out before extracting principal components – this analysis must therefore be limited

Table 5.2: Model C1a: short-run equations involving the constructed SBS factors

Short run equations	Dependent	
	d_SBS Factor 1	d_SBS Factor 2
d_SBS Factor 1 t-1	-0.0629097	-0.250320
d_SBS Factor 2 t-1	-0.0399412	-0.127386
d_log GDP deflator t-1	-14.1922	14.2779
d_log real GDP t-1	-2.82896	27.816
d_LIBOR 1m t-1	0.143102	-0.220656
d_20-year gilt yield t-1	0.240002	-0.0665184
d_log real PNFC deposits t-1	1.07614	4.71506
d_log real long term central government debt t-1	0.190477	0.432416
FTSE vol t-1	0.00693117	0.00755645
EC1	0.0173887	0.0141519

Table 5.3: Model C1b: cointegrating vectors

	Cointegrating vector 1	Cointegrating vector 2
SBS_Factor1	-1 (0)	0 (0)
SBS_Factor2	0 (0)	-1 (0)
l_gdpdef	-96.014 (23.84)	-182.45 (45.787)
l_rgdp	85.4 (20.978)	168.82 (40.291)
LIBOR_1m	0.52721 (0.22525)	2.3655 (0.43261)
ytm_20yrGilt	4.1485 (0.93516)	8.2249 (1.7961)
lr_PNFC_deposits	-20.972 (7.4514)	-34.21 (14.311)
lr_LTDebt_CG	25.086 (3.5125)	43.956 (6.7462)

Standard errors in parentheses

Table 5.4: Model C1b: short-run equations involving the constructed SBS factors

Short run equations	Dependent		
	d_SBS_Factor1	d_SBS_Factor2	d_lr_LTDebt_CG
d_SBS_Factor1_1	0.0175607	-0.320436	0.00827825
d_SBS_Factor2_1	-0.0723002	-0.0991912	0.00770703
d_l_gdpdef_1	-9.68669	10.3521	0.894
d_l_rgdp_1	-8.59420	32.8394	-0.384870
d_LIBOR_1m_1	0.130688	-0.209840	-0.00853873
d_ytm_20yrGilt_1	0.180573	-0.0147364	0.0344487*
d_lr PNFC_deposits_1	-0.192738	5.82066	-0.0952932
d_lr LTDebt_CG_1	1.09478	-0.355524	0.426481***
FTSE_Vol_1	0.00939051	0.00541357	-0.00117685**
EC1	0.216317**	-0.159179	-0.0217623***
EC2	-0.104260**	0.055255	0.00850515**

to assessing sign and significance, the coefficients having lost easy numeric interpretability. The factors also share positive relationships to the two measures of rates, and negative relationships with the measure of PNFC deposits in the traditional banking sector – offering support for Pozsar's [Pozsar, 2013] hypothesis that shadow bank money assets are substitutable with more traditional safe assets, and in support of the work of Serletis & Xu [Serletis and Xu, 2019] concerning substitutability of shadow bank services with those of traditional banks. Parameter estimates are displayed in Equations 5.1 & 5.2.

$$\begin{aligned} SBS\_Factor1 = &- 96.00 * l\_gdpdef + 85.40 * l\_rgdp \\ &+ 0.53 * LIBOR\_1m + 4.15 * ytm\_20yrGilt \\ &+ -20.98 * lr\_PNFC\_deposits + 25.09 * lr\_LT\_Debt\_CG \end{aligned} \tag{5.1}$$

$$\begin{aligned} SBS\_Factor2 = &- 182.45 * l\_gdpdef + 168.82 * l\_rgdp \\ &+ 2.37 * LIBOR\_1m + 8.22 * ytm\_20yrGilt \\ &+ -34.21 * lr\_PNFC\_deposits + 44.00 * lr\_LT\_Debt\_CG \end{aligned} \tag{5.2}$$

We also find a well-behaved system of short run equations, in which the first SBS factor (along with gilt rates and PNFC deposits) responds to disequilibrium in the second long-run equation, while disequilibrium in the first cointegrating vector prompts shifts in central government long-term debt issuance. With the exception of the error-correction terms, the SBS factors remain weakly exogenous in the short-run dynamics of this system. SBS Factor 2 however appears to contain information about the short-run response of 20-year gilt yields, and appears in that equation with significance and negative sign. Thus, increases in the value of the second shadow banking factor – which given the factor loadings we can associate with decreased issuance of money market liabilities, decreased holdings by private NFCs, and/or decreased holdings by the rest of the world, are associated with downward shifts in gilt yields in the following quarter. We reproduce the short-run equation with 20-year gilt yields as dependent herein as Equation 5.3.

$$\begin{aligned}\Delta ytm\_20yrGilt =& 50.2 + 0.06 * \Delta SBS\_Factor1_{t-1} + -0.08 * \Delta SBS\_Factor2_{t-1}\\ &+ -3.94 * \Delta l\_gdpdef_{t-1} + -2.14 * \Delta l\_rgdp_{t-1}\\ &+ 0.09\Delta * LIBOR\_1m_{t-1} + -0.23 * \Delta ytm\_20yrGilt_{t-1}\\ &+ -0.04 * \Delta lr\_PNFC\_deposits_{t-1} + -4.85 * \Delta lr\_LT\_Debt\_CG_{t-1}\\ &+ 0.001 * FTSE\_Vol_{t-1} + 0.07 * \lambda_1\\ &+ -0.07 * \lambda_2\end{aligned} \tag{5.3}$$

where as before λ_1 and λ_2 represent response to disequilibrium in the first and second long-run cointegrating vectors – the first having SBS Factor 1 as the dependent, the second having SBS Factor 2.

5.2.3 Conclusion

While the factor-augmented VECM fails to offer the strong evidence in favour of hypothesis H4 drawn from conventional VECMs, other hypotheses are better supported. GDP appears to show a positive relationship with the constructed measures of shadow banking activity, though the data transformation renders the coefficient values impossible to interpret meaningfully. The evidence for a shadow banking repsonse to opportunity cost is also inconclusive. However H3 is well supported by the long-run models, which demonstrate a negative equilibrium relationship between the measures of shadow banking activity and corporate deposits in the regulated banking sector. We are unable to demonstrate this relationship in the short-run models, perhaps suggesting that the assumption of quarter-to-quarter rigidity in demand for regulated bank deposits by corporates is too strong an assumption, and as such it is difficult to statistically disentangle supply and demand, leaving the information imparted by the quantum of shadow banking activity ambiguous. Nevertheless, the evidence for H3 is a comparable finding to that of Serletis & Xu [Serletis and Xu, 2019] who find substitutability between shadow bank and traditional bank services.

Table 5.5: Hypotheses, revisited once more

Hypothesis	Variable entering SBS money demand function	Expected sign and magnitude	Evidence from VECM models
H2	Log real GDP	+ , approximately 1	Log real GDP appears with positive sign in the long-run equilibria for the shadow banking activity factors. Due to variable abstraction it is not possible to assess the magnitude of this effect against H2.
H2	Own interest rate	+	Inconclusive - SBS factors show a positive long-run association with all measures of rates.
H2	Opportunity cost / alternative interest rates	–	Inconclusive - SBS factors show a positive long-run association with all measures of rates.
H3	Corporate deposits in traditional banking sector	– , around 1 in absolute magnitude if 'crowding out' is total	Good – the SBS factors show a negative long-run relationship with the log real level of corporate deposits in the regulated banking sector.
H4	Government debt outstanding, government debt issuance in short-run models	– , as above 1 in absolute magnitude if crowding out is total	Not demonstrated – in the long-run forms estimated here, level of government debt appears to 'crowd in' money market holdings, and the short-run relationship is inconclusive.

Serletis & Xu also document regime-switching behaviour in their paper. Applying a 2-state Markov model they find a single large state transition in the middle of the time period they study [Serletis and Xu, 2019]. We also consider the possiblity of regime-switching behaviour within our dataset, along with a relaxation of the key orthogonality assumption of the method of principal components.

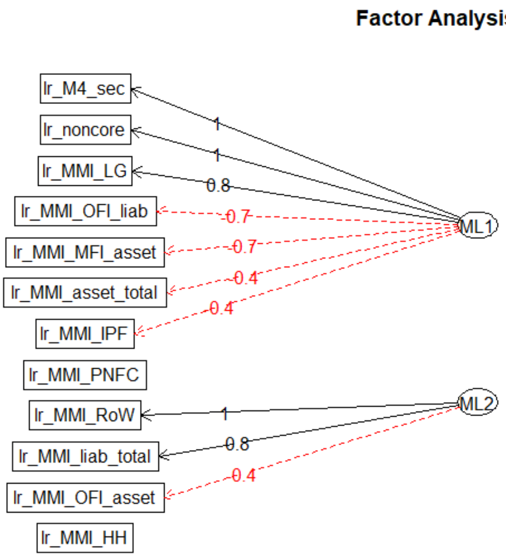
5.3 Exploratory Factor Analysis

5.3.1 Introduction and methodology

With the FAVECM producing some encouraging results in support of hypothesis H3, we further consider a more generalized study of the latent factor structure of Panel 2a, the (log real) levels data for money market instrument asset holdings by sector in the UK. We initially relax the orthogonality restraint imposed by principal components analysis in an exploratory factor analysis to check the validity of our method above; subsequently we perform a *k-means* clustering in variable space that may suggest a state-transitioning or time-varying-parameter structure like that documented by Serletis & Xu [Serletis and Xu, 2019].

The motive for this exploratory factor analysis is that the principal-component-based estimates of latent factors are constrained to be mutually uncorrelated. We exploit that characteristic above to achieve identification of our long-run cointegrating equations, but that goal may conflict with the objective of seeking latent factors that have an economic interpretation – such factors would very likely be correlated, at minimum in the time domain as macroeconomic variables broadly increase over time. We employ the same dataset, Panel 2a, as above, and with the same rationale we extract two factors by maximum likelihood. We employ the 'oblimin' rotation strategy, which seeks the simplest possible factor representation but unlike 'varimax' allows for the extracted factors to be correlated. The extracted factor representation is depicted in Figure 5.6 below.

Figure 5.6: Extracted factor representation



5.3.2 Results and discussion

In Figure 5.6 ML1 and ML2 represent the first and second factor respectively, extracted by maximum likelihood. The underlying variables are depicted at left, and the arrows give the loadings of those variables on those factors – it will be seen that these loadings are very similar to those extracted by principal components, with factor 1 loading heavily and equally on M4 securitization and noncore, while factor 2 contains information about rest of world money market holdings and, to a lesser extent, total liabilities. Further, the two factors share a low correlation of only 5%, and we can conclude that the assumption of no correlation required by principal components is valid in this case. We will return to the method of principal components for the following work.

5.4 Time-Cluster Analysis

5.4.1 Introduction and methodology

A second novel methodology we adopt, closely related to the methods of factor and principal components analysis, is cluster analysis. The general goal of cluster analysis is to classify observations into groups or sets, having the property that the members of the set are as similar as possible to one another while the sets themselves are as distinct from each other as possible. Any clustering algorithm must therefore strike a balance between within-group similarity and between-group distinction. A well-established algorithm for this purpose is k-means, sometimes known as the Lloyd-Forgy algorithm, developed at Bell Labs in the 1960s. Considering each datapoint as a location in high-dimensional space (of dimension equal to the column span of the dataset), the algorithm initializes a number of random points equal to the number of clusters desired – and so this must be exogenously given to the process.

The algorithm then alternates between two steps – assigning each observation to the cluster to whose centroid it is closest in squared Euclidean distance terms (L2 norm), and recalculating the new initial means to be the centroids of the clusters so generated. The algorithm exits and is said to have converged when the assignments, and therefore the centroids, no longer change. The initial random points may be simple random draws (known as Random Partition) or a random row from the dataset (the Forgy method), but in general there is no guarantee that the algorithm will converge to the globally optimal solution. Statistical methods exist for optimizing the number of clusters sought, but as the 'closeness' or 'distance' of points in variable space is closely related to their covariance, it is common to simply examine the 2D projection of the dataset onto the plane defined by the first two principal components – as we do here in Figure 5.7 below.

Adding the individual observations to the principal-component-space plot, we can hypothesize the existence of 3 clusters, and so initialize k-means with 3 centroids. Though we are dealing with time series, we cluster in variable space only, not in the time dimension – and so observations in the same cluster need not be consecutive or adjacent in time. Time-series-

Figure 5.7: Principal Components Analysis biplot - datapoints and loadings in PC space

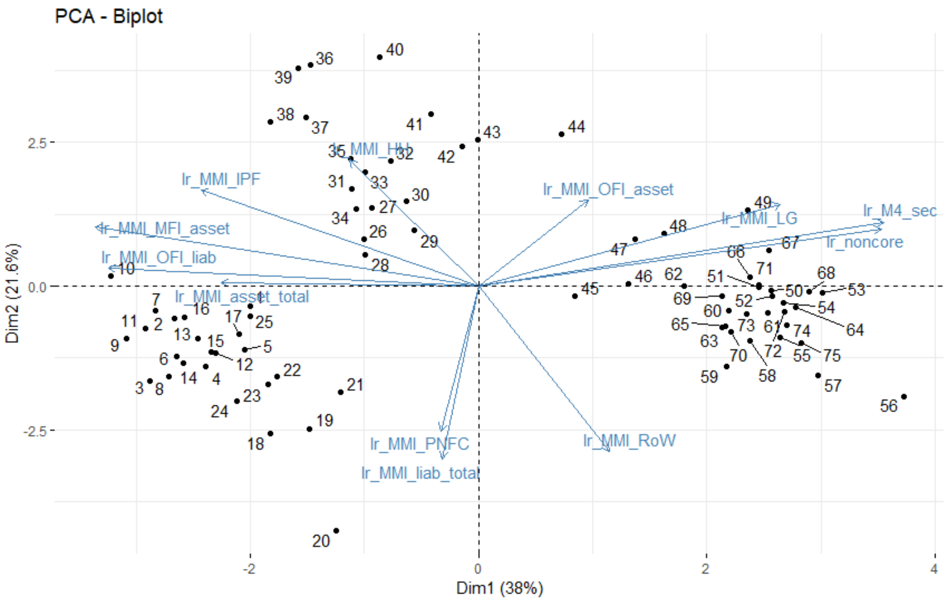
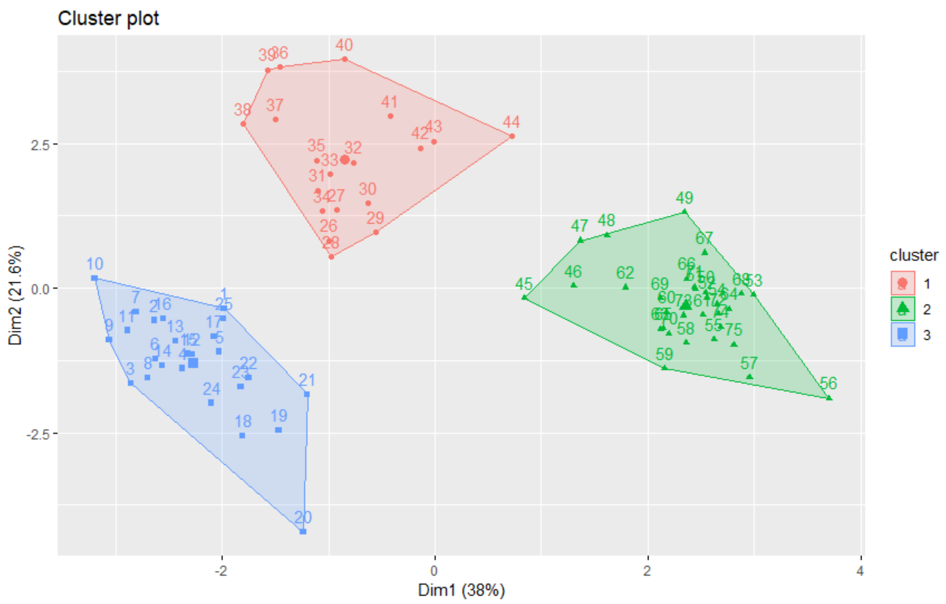


Figure 5.8: K-means cluster plot of observations in PC space



specific clustering algorithms such as Dynamic Time Warping do exist, but these aim to classify whole time series as the single unit of observation – as we are content to split the time series across observations, standard methods suffice here. Performing the 3-cluster k-means, we find the expected result, depicted in Figure 5.8.

5.4.2 Results and discussion

Though it is by no means a deterministic or typical result of this approach, it emerges in this application that all observations clustered together are also consecutive in time – cluster 3 occurs first and runs from Q4 1997 to Q4 2003, followed by Q1 from Q1 2004 to Q3 2008, and finally cluster 2 from Q4 2008 to Q2 2016. This suggests a strong state-transition structure underlying the economic relations observed here, and hints at parameter instability or nonlinearity of the type that might be assessed by a Chow or Quandt Likelihood Ratio test in traditional time series macroeconometrics. Certainly the state transition time periods are interpretable as economic regime shifts, Q4 2008 in particular. This is comparable with the single large regime shift observed in the dataset of Serletis & Xu [Serletis and Xu, 2019].

Limited degrees of freedom prevent us from fitting a full state-transition specification to the preferred vector model C1b above – however a longer or higher-frequency time-series dataset should enable this, and we highlight this as a key avenue for future research. Given the changing economic and regulatory context of shadow banking, notably before and after the financial crisis, it seems very likely to the structural parameters are time-varying, and utilizing a factor representation and a time-clustering approach would be only one of many ways to admit time-varying parameters into a macroeconomic model of the role of shadow banking in the composition of safe assets in the monetary economy.

Chapter 6

Conclusions, Limitations, and Further Study

The present work has sought to define the shadow banking sector, a growing area of study that leapt to prominence following the financial crisis, but an area in which basic questions of macroeconomic interest remain to be addressed. In particular, we highlight the role of the shadow banking sector in concealing, warehousing or otherwise obfuscating risk in order to produce 'safe' assets to meet demand unmet by sovereign issuance and not coverable by the deposit insurance provisions of traditional regulated banks. Reviewing the literature, we noted the paucity of work focusing on the UK, the relative lack of data-driven econometric studies by comparison with descriptive and thoeretical papers, and gaps in the understanding of the role of the shadow banking sector in meeting demand for safe assets. Filling these gaps in our understanding should be of interest for monetary policy makers – we established the role of the shadow banking sector in the transmission channels of monetary policy. Prudential regulators may also be interested in our work given a perception of shadow banking as a procyclical, destabilising, endogenous source of risk.

Following the methodology of Errico *et al* [Errico et al., 2014], we initially broaden our data view much beyond the shadow banking sector, considering all financial asset and liability positions observable in the UK monetary economy, from publicly-available data. Also following the recommendations of Errico *et al*, the UK's national statistical authority the ONS has begun to publish flow-of-funds matrices for the UK financial economy, and while we do not claim prior art – the contribution here is merely to arrange, not source the data – we take this as evidence that this is a relevant and important area of study. As a result of this work we are able to narrow our focus to the safe-asset juncture between the shadow banking sector and the real economy – money market instruments held on-balance-sheet by UK economic agents.

Extending a broad and deep literature concerning macroeconomic demand functions for money, the ultimate safe, liquid asset, we follow the practice in that field by employing the time-series econometric methodology of cointegration and error correction due to Engle & Granger [Engle and Granger, 1987] and to Johansen [Johansen, 1988] / Johansen & Juselius [Johansen and Juselius, 1990]. We have mixed results in attempting to replicate existing estimates of money demand functions for the UK, with a strong likelihood that parameter nonlinearity or time-instability are at cause.

Defining four groups of hypotheses firmly grounded in the existing literature on shadow banking, we are able to provide evidence for these hypotheses from our econometric study. In line with the work of Krishnamurthy & Vissing-Jorgensen [Krishnamurthy and Vissing-Jorgensen, 2012], we present evidence that shadow bank safe assets are treated as substitutable with government debt.

We subsequently extend the empirical component of the present work by studying factor representations to augment our vector time-series models, following a literature built on the work of Bernanke *et al* [Bernanke et al., 2005] and Stock & Watson [Stock and Watson, 1999, Stock and Watson, 2002, Stock and Watson, 2005]. We demonstrate a factor-augmented vector autoregression in the style of Banerjee & Marcellino [Banerjee and Marcellino, 2009] with appealing econometric qualities and offering some evidence in favour of our hypotheses. To wit, we present evidence that a long-run equilibrium relationship of negative sign exists between shadow bank activity and the volume of traditional bank deposits – that is to say that these assets are also treated as substitutable by safe-asset buyers, as hypothesised by Serletis & Xu among others [Pozsar, 2013, Serletis and Xu, 2019].

Finally, we employ a time-cluster analysis to begin to uncover the time-varying nature of the shadow banking activity factor, in the manner of Serletis & Xu [Serletis and Xu, 2019], and we demonstrate a strong 3-state transition structure, the time series split into three contiguous phases.

The key contributions of the thesis are threefold: to the shadow banking literature, to the literature concerned with money demand, and to the methodological literature concerned with factor-augmented and regime-switching models. To the shadow banking literature, we contribute the collection of a large dataset, albeit a publicly-available one. We further offer multiple time-series proxies for shadow banking activity in the UK (noncore bank funding, money-market instrument sector shares, and M4 Securitisations). We assess the predictions of theoretical and general-equilibrium modellers such as Krishnamurthy & Vissing-Jorgensen, Gennaioli *et al*, and Plantin [Krishnamurthy and Vissing-Jorgensen, 2012, Gennaioli et al., 2013, Plantin, 2014]: we show evidence that both government debt and regulated bank deposits are treated as substitutable with shadow bank deposits by safe-asset buyers.

To the literature concerned with money demand, we adopt the standard models and demonstrate a commonality between models of demand for broad money and demand for shadow bank money. Like demand for broad money, demand for shadow bank money appears to scale with real GDP, but is ambiguous with respect to the price level. We are not able to conclusively establish the response of demand for shadow bank money to opportunity cost, i.e. better interest rates available elsewhere.

To the methodological literature we offer a novel dataset and question – we are not aware of any other papers taking a factor-model, data-driven approach to assessing shadow banking. While the methodology is well-established, the object of study is not – and certainly not for the case of the UK. We also introduce a novel identification strategy for long-run equations in factor-augmented VECMs. Provided the factors have been constructed by the method of principal components, they are orthogonal by construction – and so factors extracted from the same dataset can be constrained to zero in the long-run equation normalised to any other factor extracted from the same dataset. For identification to be achieved, it suffices to include as many principal components as the rank of the full system – in the present paper, we include two principal components and have two long-run equations requiring identification. We are not aware of any other work in the field of shadow banking having implemented this methodology. The method of k-means time clustering is also believed to be novel in this field, as an atheoretic and non-parametric assessment of regime-switching behaviour in a time series.

Naturally, the present study is not without its limitations. Principally, while we have at least one model giving evidence in favour of each of our hypotheses, these are typically different and we have no single model that decisively gives evidence for all our hypotheses in a single system. Missing data, and the relatively low quarterly frequency, means that degrees of freedom can be in short supply for high-dimensional vector models, and longer or more frequently observed time series would ease this constraint. This – or a more parsimonious estimation method – would also allow for the study of time-varying structural parameters in the macroeconomic relationships governing shadow banking, which we view as the key next step in this programme of research.

Our study is also vulnerable to critiques around dataset decisions that we took – that our variables are so specific as to be a macroeconomic irrelevance, or do not capture the underlying economic activity we attribute to them. Other studies have focused on shadow banking 'in the middle' of the manufacturing process (so to speak) with repo markets, or on the origination of lending. Pozsar [Pozsar, 2014] holds that as all lending transactions inevitably involve a regulated bank somewhere along the line, only banks can create endogenous or inside money, and so it is a mistake to credit the shadow banking sector with the power to innovate unilaterally in the money supply. Our choice of the UK as the nation for study is idiosyncratic, though it does offer the opportunity for novelty when most studies focus on the US – where data is more readily available.

Certain assumptions are required to achieve identification of the econometric models – specifically, because we observe shadow banking activity in the form of quantity of financial instruments, in order to identify shifts in these quantities with shifts in demand we must deal with the matter of supply. Our assumption that alternative safe assets are subject to supply rigidity in the short term is a strong one. An instrumental variables approach may be able to achieve identification more explicitly. Also, with the exception of taking logarithms, we do not permit for nonlinearity in our functional forms – we typically seek a linear model. We also estimate equilibrating relationships across the whole time series, when in fact regime switches seem very likely to be at play – as demonstrated by our time-clustering model. Future researchers may wish to consider relaxing any or all of these assumptions and constraints in search of better models of the behaviour of the shadow banking sector in response to demand for safe assets.

Nevertheless, we believe our results should be of interest to academics and policymakers. We have documented the existence of a shadow banking sector in the UK, which scales activity up and down at the margin depending upon the availability of safe-asset substitutes. While we were unable to conclusively demonstrate a link with policy interest rates, we believe the shadow banking sector to be important in the transmission channel of monetary policy. We also believe that the response to demand for safe assets should be of interest to regulators charged with supervising the health of the banking system – when government debt or bank deposits, for whatever reason, are insufficient to meet demand for safety, activity will increase in the dimly-lit, lightly-regulated, fragile, and procyclical shadow banking sector.

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Appendix A

Regression Model Output

A.1 Group A Hypotheses

A.1.1 A1, Models of M0 notes & coins

Variables of interest

A1a, log real M0 dependent, contemporaneous OLS with log real GDP, log GDP deflator (price level), 20-year gilt yield (level)

A1a: OLS, using observations 2000:1–2016:2 ($T = 66$)
Dependent variable: l_realM0

	Coefficient	Std. Error	t-ratio	p-value
const	−2.02091	1.18497	−1.705	0.0931
l_rgdp	0.230969	0.118109	1.956	0.0550
l_gdpdef	1.22102	0.0986565	12.38	0.0000
yrGilt	−0.0333071	0.00641835	−5.189	0.0000

Mean dependent var	6.318674	S.D. dependent var	0.164152
Sum squared resid	0.041353	S.E. of regression	0.025826
R^2	0.976390	Adjusted R^2	0.975247
$F(3, 62)$	854.6552	P-value(F)	2.31e–50
Log-likelihood	149.7337	Akaike criterion	−291.4674
Schwarz criterion	−282.7088	Hannan–Quinn	−288.0065
$\hat{\rho}$	0.831678	Durbin–Watson	0.271744

Figure A.1: Log Real M0 notes & coins

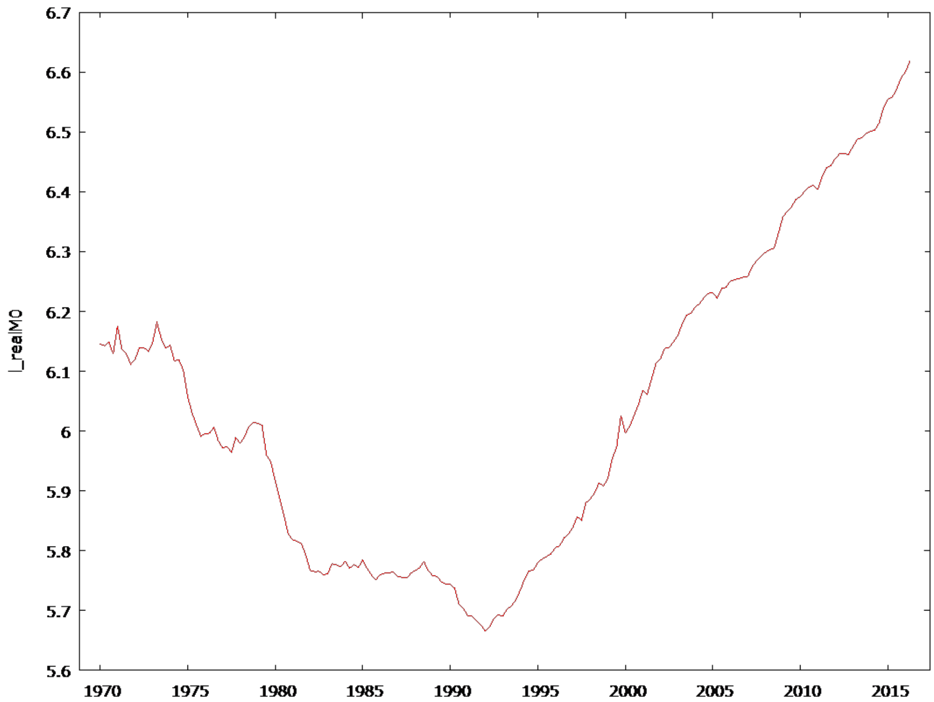


Figure A.2: Log Real GDP

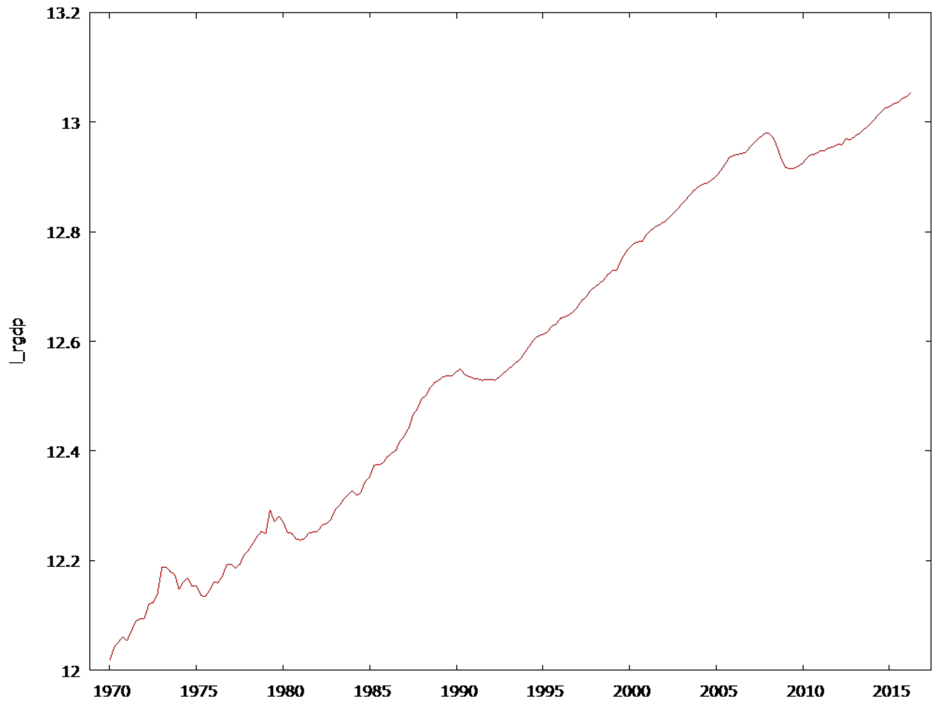


Figure A.3: Log of GDP Deflator

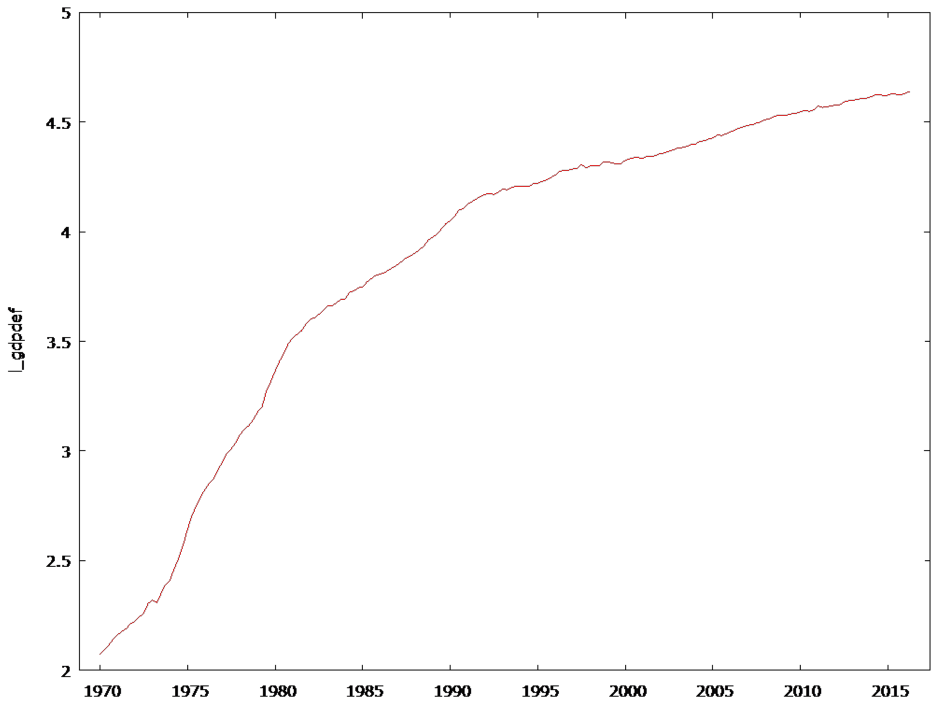


Figure A.4: 10-year (yrGilt1) and 20-year (yrGilt) gilt yields

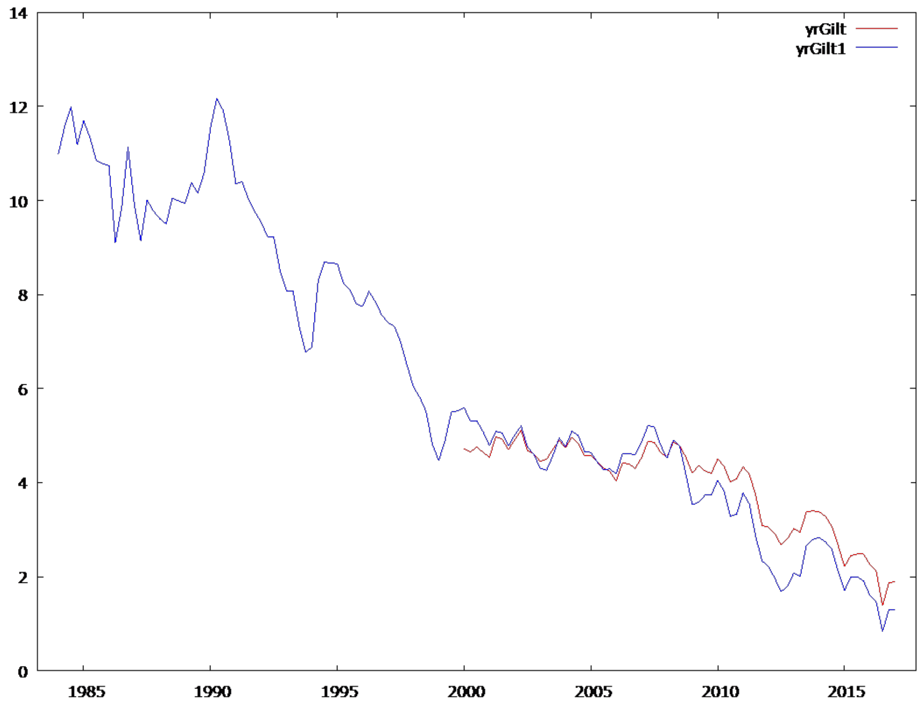


Figure A.5: RPI, annual percentage change

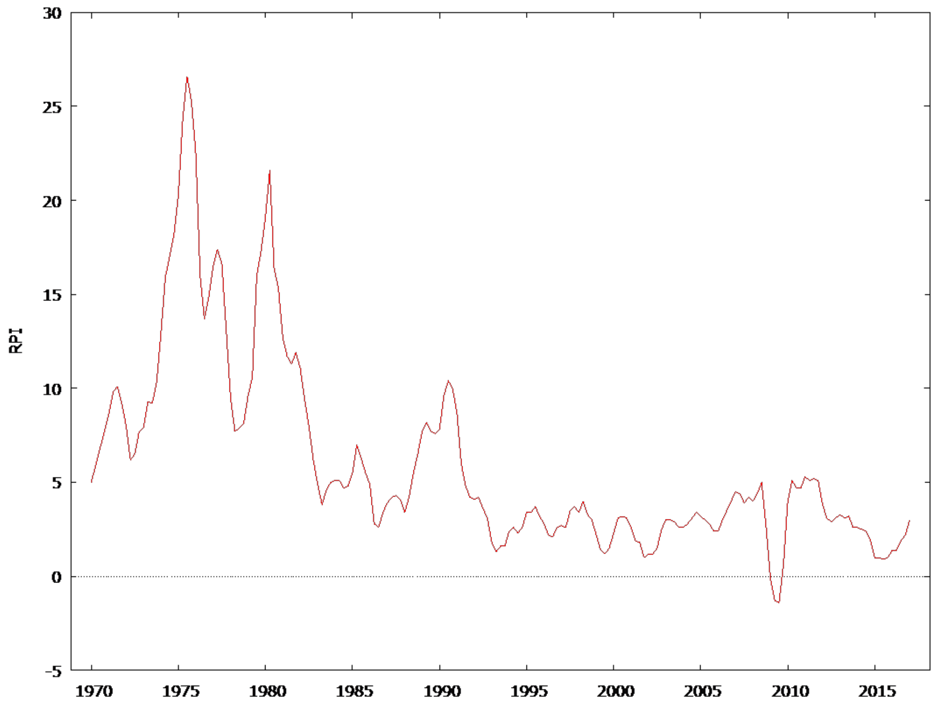
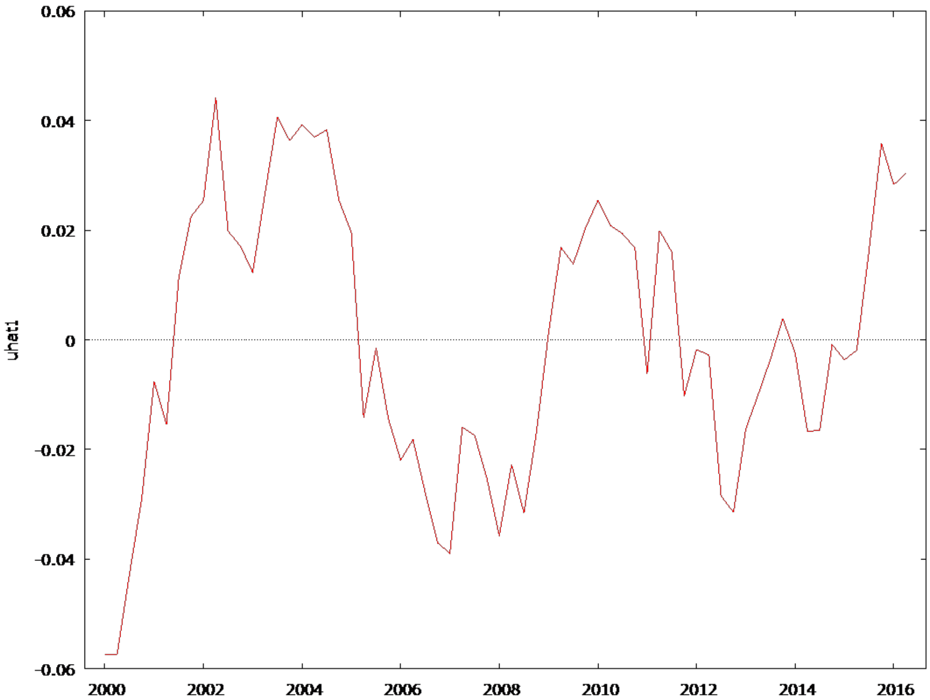


Figure A.6: A1a, residual time-series plot

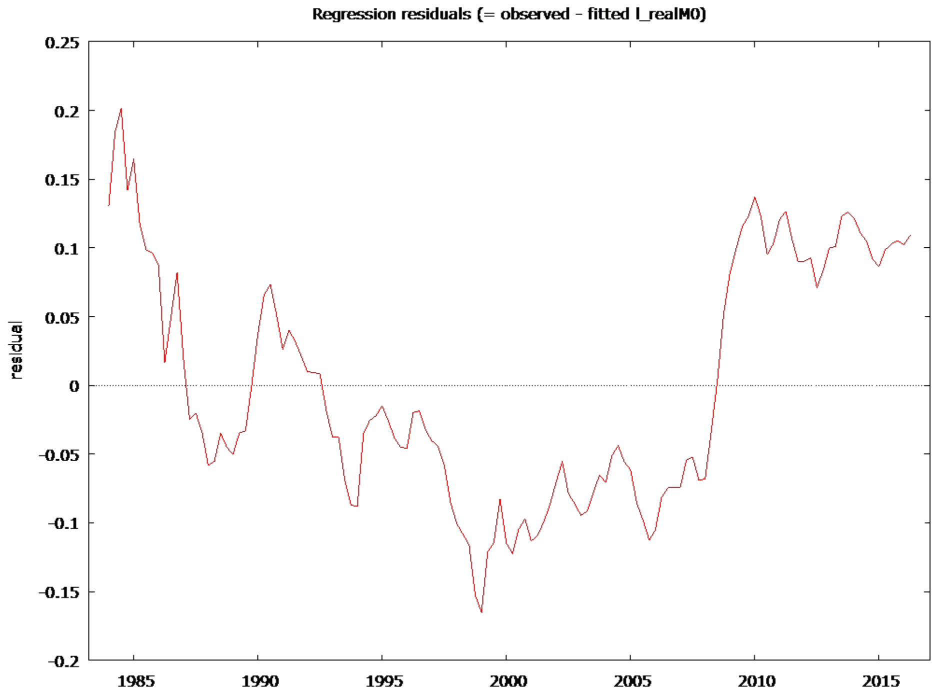


A1b, log real M0 dependent, contemporaneous OLS with log real GDP, log GDP deflator (price level), 10-year gilt yield (level)

A1b: OLS, using observations 1984:1–2016:2 (T = 130)
Dependent variable: l_realM0

	Coefficient	Std. Error	t-ratio	p-value
const	−12.7990	1.84347	−6.943	0.0000
l_rgdp	1.79672	0.168915	10.64	0.0000
l_gdpdef	−0.880605	0.120987	−7.279	0.0000
yrGilt1	−0.0405174	0.00820433	−4.939	0.0000

Figure A.7: A1b, residual time-series plot



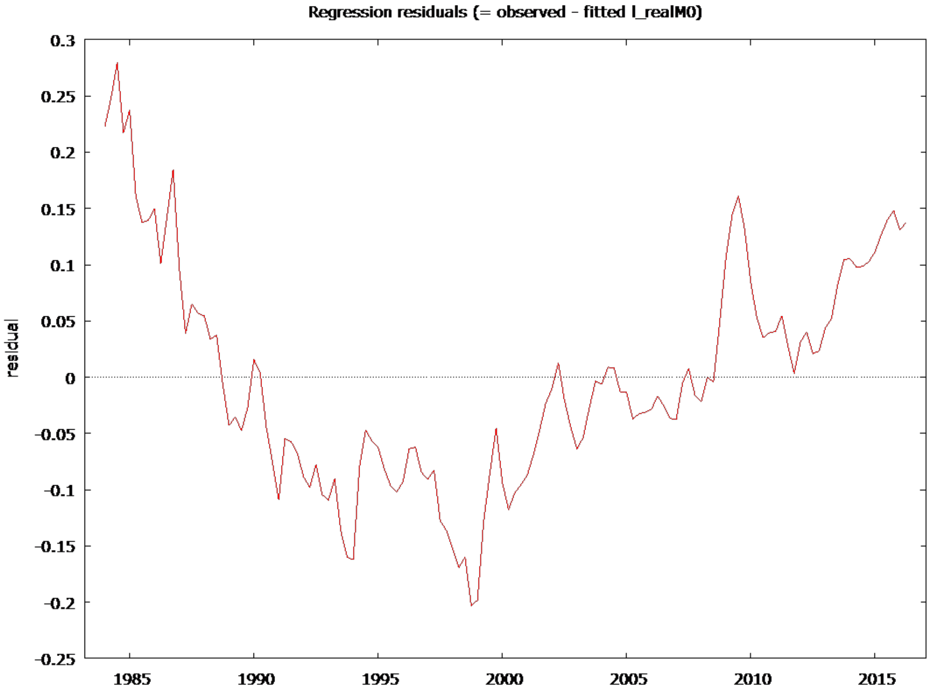
Mean dependent var	6.052984	S.D. dependent var	0.299578
Sum squared resid	0.967779	S.E. of regression	0.087640
R^2	0.916408	Adjusted R^2	0.914417
$F(3, 126)$	460.4381	P-value(F)	1.08e–67
Log-likelihood	134.0566	Akaike criterion	−260.1131
Schwarz criterion	−248.6430	Hannan–Quinn	−255.4524
$\hat{\rho}$	0.966484	Durbin–Watson	0.060896

A1c, log real M0 dependent, contemporaneous OLS with log real GDP, RPI inflation (% per annum), 10-year gilt yield (level)

A1c: OLS, using observations 1984:1–2016:2 (T = 130)

Dependent variable: l_realM0

Figure A.8: A1c, residual time-series plot



	Coefficient	Std. Error	t-ratio	p-value
const	−2.26121	1.98725	−1.138	0.2573
l_rgdp	0.673638	0.151231	4.454	0.0000
RPI	0.0193701	0.00619177	3.128	0.0022
yrGilt1	−0.0529921	0.0117588	−4.507	0.0000

Mean dependent var	6.052984	S.D. dependent var	0.299578
Sum squared resid	1.275603	S.E. of regression	0.100617
R^2	0.889819	Adjusted R^2	0.887196
$F(3, 126)$	339.1916	P-value(F)	3.82e–60
Log-likelihood	116.1055	Akaike criterion	−224.2110
Schwarz criterion	−212.7408	Hannan–Quinn	−219.5503
$\hat{\rho}$	0.946952	Durbin–Watson	0.080439

Table A.1: Information criteria for lag selection, system A1d

lags	loglik	p(LR)	AIC	BIC	HQC
1	671.21559		-10.675665	-10.215990	-10.488959
2	734.86702	0.00000	-11.456836	-10.629420*	-11.120766*
3	749.85749	0.01810	-11.440287	-10.245130	-10.954851
4	766.94405	0.00515	-11.458099	-9.895202	-10.823299
5	787.31869	0.00060	-11.529815	-9.599177	-10.745649
6	809.34827	0.00019	-11.628660*	-9.330282	-10.695130
7	823.99566	0.02202	-11.606486	-8.940368	-10.523592
8	832.69189	0.36065	-11.486752	-8.452893	-10.254493

A1d, VECM system on log real M0, log real GDP, RPI level, 10-year gilt yield level

VAR lag selection for system A1d

Table A.2: Trace and maximum eigenvalue tests for system A1d

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.40823	124.78 [0.0000]	67.154 [0.0000]
1	0.20877	57.630 [0.0000]	29.973 [0.0015]
2	0.19406	27.656 [0.0003]	27.615 [0.0001]
3	0.00032337	0.041398 [0.8388]	0.041398 [0.8388]

Johansen rank selection for system A1d

Model A1d

VECM system, lag order 2

Maximum likelihood estimates, observations 1984:3–2016:2 ($T = 128$)

Cointegration rank = 3

Case 3: Unrestricted constant

Restrictions on beta: b[1,1] = -1 b[2,2] = -1 b[3,3] = -1

Cointegrating vectors

l_realM0$_{t-1}$	1.00000	−0.0151742	−11.4217
l_rgdp$_{t-1}$	0.576930	1.00000	−0.843360
RPI$_{t-1}$	0.241855	−0.0137198	1.00000
yrGilt1$_{t-1}$	0.161216	0.0640785	−1.80388

Adjustment vectors

l_realM0$_{t-1}$	1.00000	0.172926	−0.0120991
l_rgdp$_{t-1}$	0.154549	1.00000	0.00496597
RPI$_{t-1}$	33.8217	−29.2986	1.00000
yrGilt1$_{t-1}$	11.5545	28.4149	−0.221770

Log-likelihood = 756.938

Determinant of covariance matrix = 8.58286e–011

AIC = −11.2647

BIC = −10.4625

HQC = −10.9387

Equation 1: Δl_realM0

	Coefficient	Std. Error	t-ratio	p-value
const	0.392516	0.203993	1.924	0.0566
d_l_realM0_1	−0.162161	0.0885569	−1.831	0.0695
d_l_rgdp_1	−0.241354	0.145159	−1.663	0.0989
ΔRPI_{t-1}	0.000388793	0.00120483	0.3227	0.7475
$\Delta\text{yrGilt1}_{t-1}$	0.00307347	0.00218397	1.407	0.1619
EC1	0.0112620	0.00164196	6.859	0.0000
EC2	0.00675067	0.0152094	0.4438	0.6579
EC3	−0.00140624	0.000472403	−2.977	0.0035

Mean dependent var	0.006624	S.D. dependent var	0.011339
Sum squared resid	0.010778	S.E. of regression	0.009361
R^2	0.339930	Adjusted R^2	0.318464
$\hat{\rho}$	−0.026731	Durbin–Watson	2.048188

Equation 2: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.487275	0.105440	4.621	0.0000
d_l_realM0_1	0.0426092	0.0457735	0.9309	0.3537
d_l_rgdp_1	0.356129	0.0750299	4.747	0.0000
ΔRPI_{t-1}	0.000846155	0.000622755	1.359	0.1767
$\Delta\text{yrGilt1}_{t-1}$	0.00143990	0.00112886	1.276	0.2045
EC1	0.00174053	0.000848699	2.051	0.0424
EC2	0.0390379	0.00786147	4.966	0.0000
EC3	0.000577177	0.000244177	2.364	0.0197

Mean dependent var	0.005742	S.D. dependent var	0.006464
Sum squared resid	0.002879	S.E. of regression	0.004838
R^2	0.457434	Adjusted R^2	0.439790
$\hat{\rho}$	−0.068122	Durbin–Watson	2.135652

Equation 3: ΔRPI

	Coefficient	Std. Error	t-ratio	p-value
const	−19.3012	13.3102	−1.450	0.1496
d_l_realM0_1	−5.12637	5.77821	−0.8872	0.3767
d_l_rgdp_1	12.4812	9.47138	1.318	0.1900
ΔRPI$_{t-1}$	0.512585	0.0786134	6.520	0.0000
ΔyrGilt1$_{t-1}$	0.111888	0.142501	0.7852	0.4339
EC1	0.380900	0.107135	3.555	0.0005
EC2	−1.14375	0.992392	−1.153	0.2513
EC3	0.116226	0.0308236	3.771	0.0003

Mean dependent var	−0.028906	S.D. dependent var	0.801490
Sum squared resid	45.88417	S.E. of regression	0.610772
R^2	0.437577	Adjusted R^2	0.419287
$\hat{\rho}$	0.041431	Durbin–Watson	1.909041

Equation 4: ΔyrGilt1

	Coefficient	Std. Error	t-ratio	p-value
const	18.6449	9.31051	2.003	0.0474
d_l_realM0_1	−3.36837	4.04186	−0.8334	0.4063
d_l_rgdp_1	−1.70718	6.62524	−0.2577	0.7971
ΔRPI$_{t-1}$	−0.0193206	0.0549901	−0.3513	0.7259
ΔyrGilt1$_{t-1}$	0.214768	0.0996797	2.155	0.0331
EC1	0.130127	0.0749413	1.736	0.0850
EC2	1.10926	0.694179	1.598	0.1126
EC3	−0.0257756	0.0215612	−1.195	0.2342

Mean dependent var	−0.078935	S.D. dependent var	0.435720
Sum squared resid	22.45119	S.E. of regression	0.427235
R^2	0.068846	Adjusted R^2	0.038565
$\hat{\rho}$	0.034429	Durbin–Watson	1.925528

Figure A.9: Log real M4

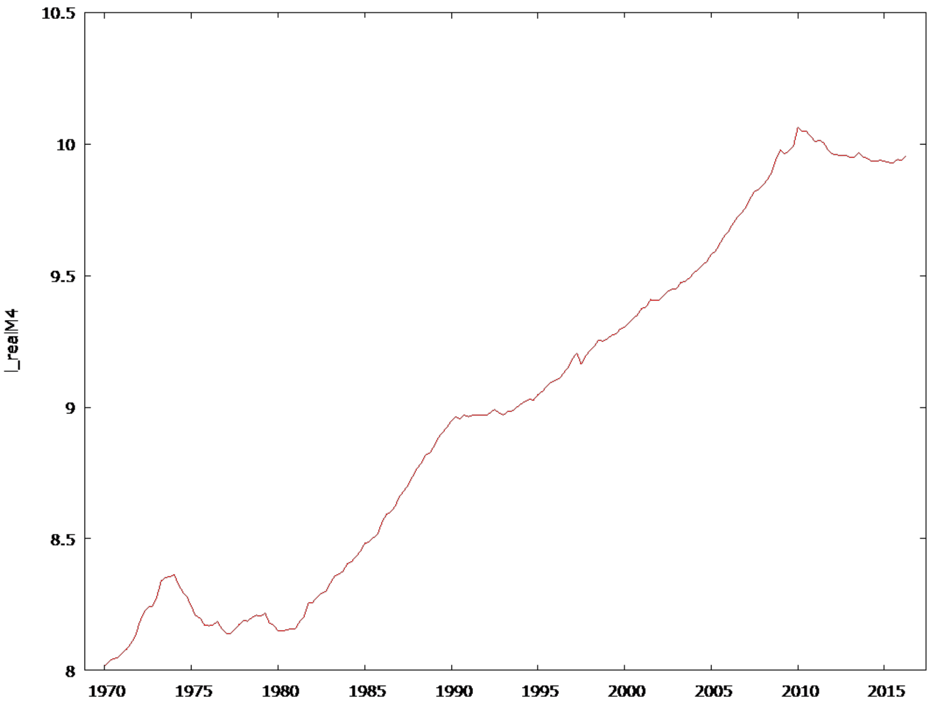


Figure A.10: Bank of England base rate

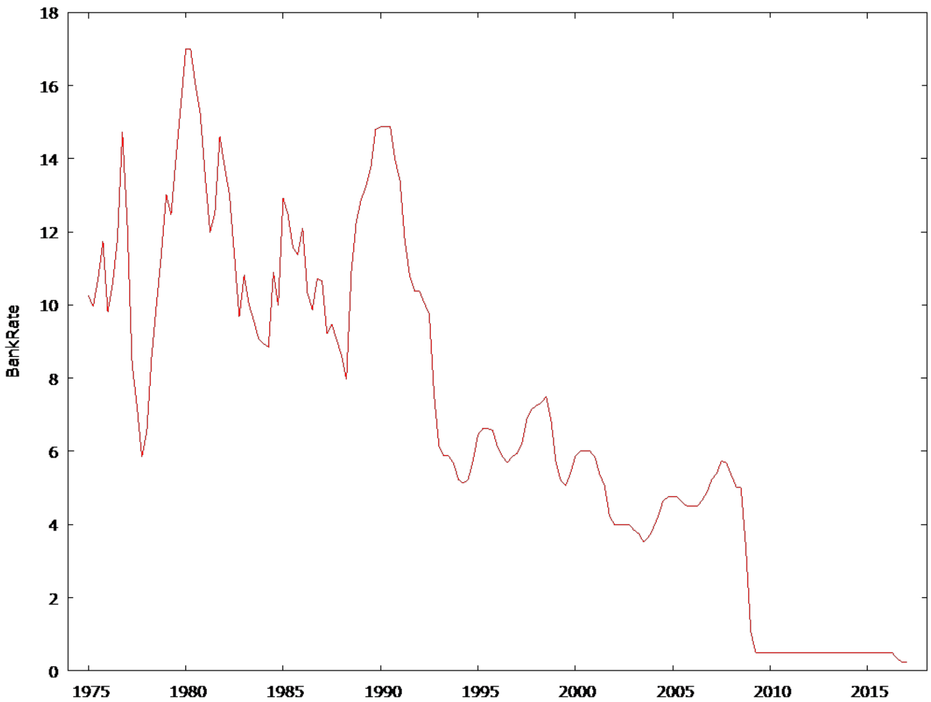
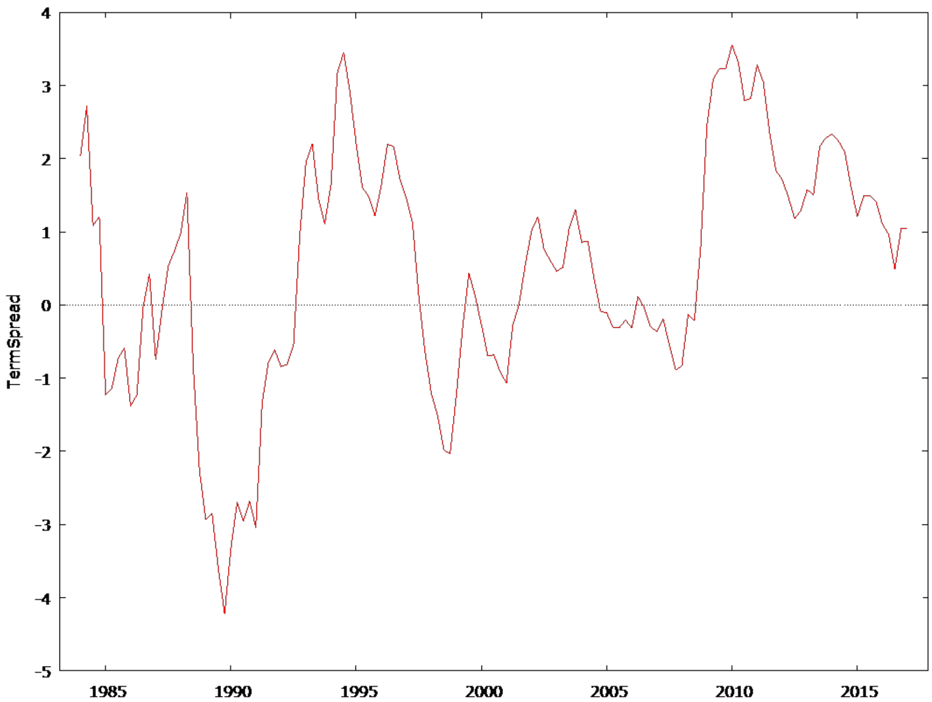


Figure A.11: Term Spread



A.1.2 A2, Models of M4 broad money

Variables of interest

A2a, log real M4 dependent, contemporaneous OLS with log real GDP, log GDP deflator, 20-year gilt yield

A2a: OLS, using observations 2000:1–2016:2 ($T = 66$)
Dependent variable: l_realM4

	Coefficient	Std. Error	t-ratio	p-value
const	4.38405	2.20791	1.986	0.0515
l_rgdp	−0.921665	0.220067	−4.188	0.0001
l_gdpdef	3.73590	0.183823	20.32	0.0000
yrGilt	0.120728	0.0119591	10.10	0.0000

Mean dependent var	9.754190	S.D. dependent var	0.242639
Sum squared resid	0.143568	S.E. of regression	0.048121
R^2	0.962484	Adjusted R^2	0.960668
$F(3, 62)$	530.2023	P-value(F)	3.95e–44
Log-likelihood	108.6600	Akaike criterion	−209.3199
Schwarz criterion	−200.5613	Hannan–Quinn	−205.8590
$\hat{\rho}$	0.684255	Durbin–Watson	0.620972

A2b, log real M4 dependent, contemporaneous OLS with log real GDP, log GDP deflator, 10-year gilt yield

A2b: OLS, using observations 1984:1–2016:2 ($T = 130$)
Dependent variable: l_realM4

	Coefficient	Std. Error	t-ratio	p-value
const	−12.1295	1.94380	−6.240	0.0000
l_rgdp	1.44301	0.178109	8.102	0.0000
l_gdpdef	0.713900	0.127572	5.596	0.0000
yrGilt1	0.00387092	0.00865086	0.4475	0.6553

Mean dependent var	9.343253	S.D. dependent var	0.485480
Sum squared resid	1.075991	S.E. of regression	0.092410
R^2	0.964610	Adjusted R^2	0.963768
$F(3, 126)$	1144.787	P-value(F)	3.36e–91
Log-likelihood	127.1670	Akaike criterion	−246.3340
Schwarz criterion	−234.8638	Hannan–Quinn	−241.6733
$\hat{\rho}$	0.977833	Durbin–Watson	0.044233

A2c, log real M4 dependent, contemporaneous OLS with log real GDP, RPI inflation, 10-year gilt yield

A2c: OLS, using observations 1984:1–2016:2 (T = 130)
Dependent variable: l_realM4

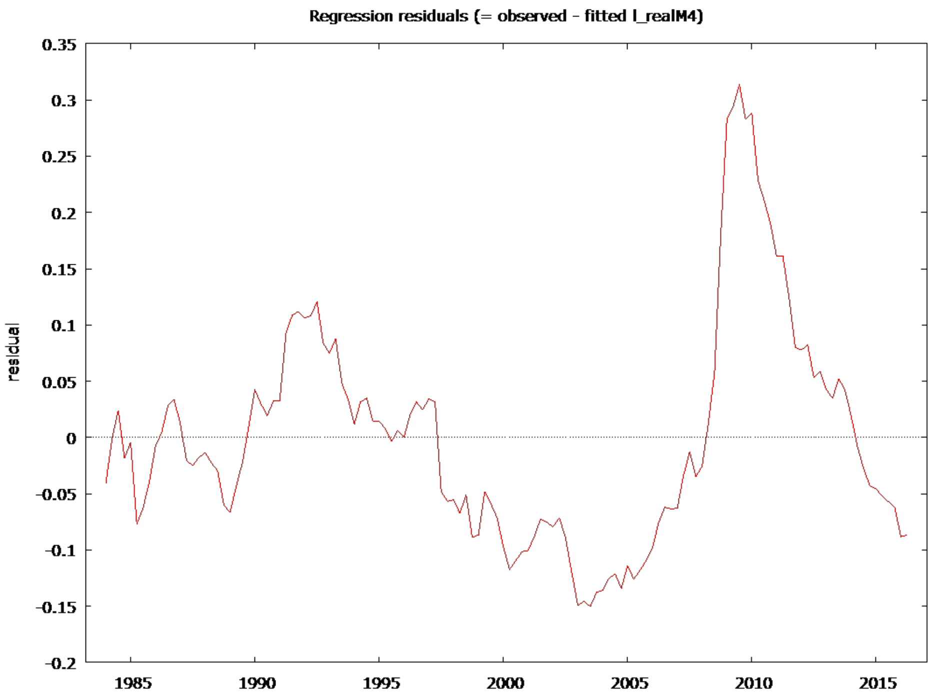
	Coefficient	Std. Error	t-ratio	p-value
const	−15.4105	1.96811	−7.830	0.0000
l_rgdp	1.95088	0.149774	13.03	0.0000
yrGilt1	−0.0261071	0.0116455	−2.242	0.0267
RPI	0.0186921	0.00613214	3.048	0.0028

Mean dependent var	9.343253	S.D. dependent var	0.485480
Sum squared resid	1.251153	S.E. of regression	0.099648
R^2	0.958849	Adjusted R^2	0.957869
$F(3, 126)$	978.6370	P-value(F)	4.48e–87
Log-likelihood	117.3635	Akaike criterion	−226.7270
Schwarz criterion	−215.2568	Hannan–Quinn	−222.0663
$\hat{\rho}$	0.966441	Durbin–Watson	0.071366

A2d, log real M4 dependent, contemporaneous OLS with log real GDP, RPI inflation, 10-year gilt yield, LIBOR

A2d: OLS, using observations 1984:1–2016:2 (T = 130)
Dependent variable: l_realM4

Figure A.12: A2c, residual time-series plot



	Coefficient	Std. Error	t-ratio	p-value
const	−14.6115	2.10551	−6.940	0.0000
l_rgdp	1.66504	0.192071	8.669	0.0000
l_gdpdef	0.617276	0.129459	4.768	0.0000
yrGilt1	0.0331322	0.0136929	2.420	0.0170
LIBOR	−0.0187619	0.00691345	−2.714	0.0076

Mean dependent var	9.343253	S.D. dependent var	0.485480
Sum squared resid	1.016122	S.E. of regression	0.090161
R^2	0.966579	Adjusted R^2	0.965510
$F(4,125)$	903.8034	P-value(F)	3.46e–91
Log-likelihood	130.8882	Akaike criterion	−251.7763
Schwarz criterion	−237.4386	Hannan–Quinn	−245.9504
$\hat{\rho}$	0.971128	Durbin–Watson	0.060120

A2e, log real M4 dependent, contemporaneous OLS with log real GDP, RPI inflation, 10-year gilt yield, Bank of England Base Rate

A2e: OLS, using observations 1984:1–2016:2 ($T = 130$)
Dependent variable: l_realM4

	Coefficient	Std. Error	t-ratio	p-value
const	−14.5787	1.97809	−7.370	0.0000
l_rgdp	1.66421	0.180946	9.197	0.0000
l_gdpdef	0.609170	0.125330	4.861	0.0000
yrGilt1	0.0350726	0.0119742	2.929	0.0040
BankRate	−0.0199387	0.00553559	−3.602	0.0005

Mean dependent var	9.343253	S.D. dependent var	0.485480
Sum squared resid	0.974815	S.E. of regression	0.088309
R^2	0.967938	Adjusted R^2	0.966912
$F(4,125)$	943.4257	P-value(F)	2.59e–92
Log-likelihood	133.5857	Akaike criterion	−257.1714
Schwarz criterion	−242.8338	Hannan–Quinn	−251.3456
$\hat{\rho}$	0.962098	Durbin–Watson	0.078667

A2f, log real M4 dependent, contemporaneous OLS with log real GDP, RPI inflation, 10-year gilt yield, Term Spread (10-year yield minus Base Rate)

A2f: OLS, using observations 1984:1–2016:2 ($T = 130$)
Dependent variable: l_realM4

	Coefficient	Std. Error	t-ratio	p-value
const	−14.5787	1.97809	−7.370	0.0000
l_rgdp	1.66421	0.180946	9.197	0.0000
l_gdpdef	0.609170	0.125330	4.861	0.0000
BankRate	0.0151339	0.00883858	1.712	0.0893
TermSpread	0.0350726	0.0119742	2.929	0.0040

Mean dependent var	9.343253	S.D. dependent var	0.485480
Sum squared resid	0.974815	S.E. of regression	0.088309
R^2	0.967938	Adjusted R^2	0.966912
$F(4, 125)$	943.4257	P-value(F)	2.59e–92
Log-likelihood	133.5857	Akaike criterion	−257.1714
Schwarz criterion	−242.8338	Hannan–Quinn	−251.3456
$\hat{\rho}$	0.962098	Durbin–Watson	0.078667

A2g, VECM system on log real M4 dependent, log real GDP, RPI inflation, 10-year gilt yield, Bank of England Base Rate)

VAR lag selection for system A2g

Table A.3: Information criteria for lag selection, system A2g

lags	loglik	p(LR)	AIC	BIC	HQC
1	561.80784		-8.718161	-8.028648	-8.438102
2	633.03810	0.00000	-9.476034	-8.211926*	-8.962593*
3	661.70413	0.00024	-9.536133	-7.697431	-8.789309
4	685.63034	0.00388	-9.518530	-7.105233	-8.538324
5	717.76446	0.00003	-9.635483	-6.647592	-8.421894
6	743.64081	0.00129	-9.649849*	-6.087364	-8.202878
7	763.20248	0.03580	-9.560696	-5.423616	-7.880342
8	787.68058	0.00286	-9.552141	-4.840466	-7.638404

Table A.4: Trace and maximum eigenvalue tests for system A2g

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.40081	157.09 [0.0000]	65.558 [0.0000]
1	0.28752	91.533 [0.0000]	43.392 [0.0001]
2	0.16968	48.141 [0.0001]	23.801 [0.0183]
3	0.16364	24.340 [0.0014]	22.874 [0.0012]
4	0.011387	1.4659 [0.2260]	1.4659 [0.2260]

Johansen rank selection for system A2g

Model A2g

VECM system, lag order 2

Maximum likelihood estimates, observations 1984:3–2016:2 ($T = 128$)

Cointegration rank = 4

Case 3: Unrestricted constant

Restrictions on beta: b[1,1] = -1 b[2,2] = -1 b[3,3] = -1 b[4,4] = -1

Cointegrating vectors

l_realM4$_{t-1}$	1.00000	−1.94023	50.6276	−2.14471
l_rgdp$_{t-1}$	−0.911490	1.00000	−177.137	11.1956
RPI$_{t-1}$	−0.111096	−0.0478950	1.00000	0.0536435
yrGilt1$_{t-1}$	0.0522684	−0.0807639	−2.97725	1.00000
BankRate$_{t-1}$	0.0629579	−0.0671178	−2.37287	−0.444878

Adjustment vectors

l_realM4$_{t-1}$	1.00000	1.70074	−0.0765620	0.00182400
l_rgdp$_{t-1}$	−0.0829001	1.00000	0.0151717	0.00589447
RPI$_{t-1}$	181.771	31.6822	1.00000	−0.368823
yrGilt1$_{t-1}$	−17.8581	19.0595	−0.0598497	1.00000
BankRate$_{t-1}$	−65.3581	50.9624	0.207558	−1.42342

Log-likelihood = 637.907

Determinant of covariance matrix = 3.22763e–011

AIC = −9.1079

BIC = −7.8824

HQC = −8.6100

Equation 1: Δl_realM4

	Coefficient	Std. Error	t-ratio	p-value
const	−0.918447	0.361536	−2.540	0.0123
d_l_realM4_1	0.0890399	0.0842507	1.057	0.2927
d_l_rgdp_1	−0.545268	0.231719	−2.353	0.0202
$\Delta \mathrm{RPI}_{t-1}$	0.00622877	0.00193128	3.225	0.0016
$\Delta \mathrm{yrGilt1}_{t-1}$	0.000107026	0.00333006	0.03214	0.9744
$\Delta \mathrm{BankRate}_{t-1}$	−0.000972555	0.00222573	−0.4370	0.6629
EC1	−0.0139394	0.0101400	−1.375	0.1717
EC2	−0.0130519	0.00382223	−3.415	0.0009
EC3	0.000594869	0.000138566	4.293	0.0000
EC4	0.000269878	0.00204074	0.1322	0.8950

Mean dependent var	0.012054	S.D. dependent var	0.015942
Sum squared resid	0.022717	S.E. of regression	0.013646
R^2	0.296204	Adjusted R^2	0.267360
$\hat{\rho}$	−0.021708	Durbin–Watson	2.042263

Equation 2: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.375521	0.124864	3.007	0.0032
d_l_realM4_1	0.0175548	0.0290978	0.6033	0.5474
d_l_rgdp_1	0.287895	0.0800293	3.597	0.0005
$\Delta \mathrm{RPI}_{t-1}$	9.35278e–006	0.000667010	0.01402	0.9888
$\Delta \mathrm{yrGilt1}_{t-1}$	0.000725344	0.00115011	0.6307	0.5294
$\Delta \mathrm{BankRate}_{t-1}$	0.00200378	0.000768705	2.607	0.0103
EC1	0.00115558	0.00350207	0.3300	0.7420
EC2	−0.00767426	0.00132009	−5.813	0.0000
EC3	−0.000117880	4.78568e–005	−2.463	0.0152
EC4	0.000872141	0.000704815	1.237	0.2183

Mean dependent var	0.005742	S.D. dependent var	0.006464
Sum squared resid	0.002710	S.E. of regression	0.004713
R^2	0.489403	Adjusted R^2	0.468477
$\hat{\rho}$	−0.019724	Durbin–Watson	2.038601

Equation 3: ΔRPI

	Coefficient	Std. Error	t-ratio	p-value
const	13.6517	15.6909	0.8700	0.3860
d_l_realM4_1	−4.12123	3.65654	−1.127	0.2619
d_l_rgdp_1	20.5047	10.0568	2.039	0.0436
ΔRPI_{t-1}	0.477566	0.0838190	5.698	0.0000
$\Delta\text{yrGilt1}_{t-1}$	0.0576436	0.144527	0.3988	0.6907
$\Delta\text{BankRate}_{t-1}$	0.223571	0.0965984	2.314	0.0223
EC1	−2.53378	0.440084	−5.757	0.0000
EC2	−0.243137	0.165887	−1.466	0.1453
EC3	−0.00776977	0.00601387	−1.292	0.1988
EC4	−0.0545707	0.0885697	−0.6161	0.5390

Mean dependent var	−0.028906	S.D. dependent var	0.801490
Sum squared resid	42.79082	S.E. of regression	0.592237
R^2	0.475494	Adjusted R^2	0.453998
$\hat{\rho}$	−0.052315	Durbin–Watson	2.103078

Equation 4: ΔyrGilt1

	Coefficient	Std. Error	t-ratio	p-value
const	18.2900	10.9024	1.678	0.0960
d_l_realM4_1	−1.23949	2.54065	−0.4879	0.6265
d_l_rgdp_1	−1.74161	6.98769	−0.2492	0.8036
ΔRPI_{t-1}	0.0686298	0.0582394	1.178	0.2409
$\Delta\text{yrGilt1}_{t-1}$	0.320304	0.100421	3.190	0.0018
$\Delta\text{BankRate}_{t-1}$	−0.219208	0.0671189	−3.266	0.0014
EC1	0.248932	0.305781	0.8141	0.4172
EC2	−0.146268	0.115263	−1.269	0.2069
EC3	0.000465018	0.00417858	0.1113	0.9116
EC4	0.147959	0.0615404	2.404	0.0177

Mean dependent var	−0.078935	S.D. dependent var	0.435720
Sum squared resid	20.65856	S.E. of regression	0.411500
R^2	0.143195	Adjusted R^2	0.108080
$\hat{\rho}$	0.099762	Durbin–Watson	1.796765

Equation 5: ΔBankRate

	Coefficient	Std. Error	t-ratio	p-value
const	−22.9879	16.4136	−1.401	0.1639
d_l_realM4_1	−2.73248	3.82495	−0.7144	0.4764
d_l_rgdp_1	0.903511	10.5200	0.08589	0.9317
ΔRPI$_{t-1}$	0.155939	0.0876796	1.779	0.0778
ΔyrGilt1$_{t-1}$	0.206807	0.151184	1.368	0.1739
ΔBankRate$_{t-1}$	0.0283991	0.101048	0.2810	0.7792
EC1	0.911055	0.460353	1.979	0.0501
EC2	−0.391099	0.173528	−2.254	0.0260
EC3	−0.00161268	0.00629086	−0.2564	0.7981
EC4	−0.210609	0.0926492	−2.273	0.0248

Mean dependent var	−0.065270	S.D. dependent var	0.693708
Sum squared resid	46.82338	S.E. of regression	0.619514
R^2	0.233865	Adjusted R^2	0.202466
$\hat{\rho}$	0.070693	Durbin–Watson	1.828528

A.2 Group B Hypotheses

A.2.1 Variables of interest

A.2.2 B1, Models of log real Money Market Instruments that are liabilities of Other Financial Institutions (logreal_B1)

B1a, log real B1 dependent, contemporaneous OLS with log real GDP, RPI, 10-year gilt yield

B1a: OLS, using observations 1987:1–2016:2 ($T = 118$)
Dependent variable: logreal_B1

	Coefficient	Std. Error	t-ratio	p-value
const	−10.5273	5.47665	−1.922	0.0571
l_rgdp	1.20814	0.417238	2.896	0.0045
RPI	−0.0852940	0.0160438	−5.316	0.0000
ytm_10yrGilt	0.0174733	0.0309267	0.5650	0.5732

Figure A.13: MMIs_OFIs_liab (Total economy balance sheet, Money Market Instruments that are liabilities of Other Financial Institutions, £m

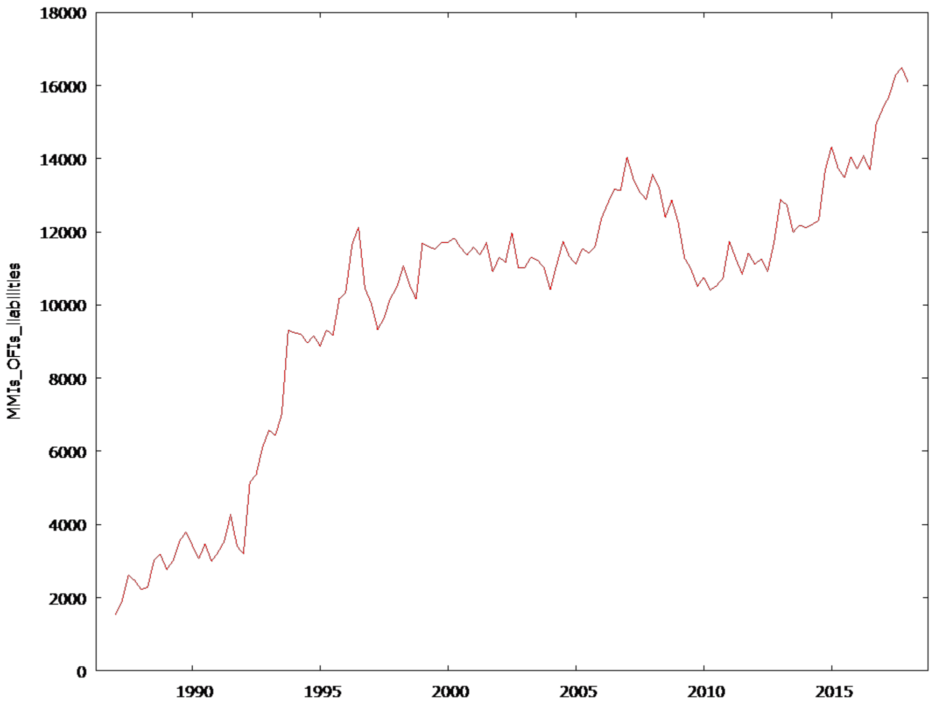


Figure A.14: logreal_B1 (log of MMIs_OFIs_liab deflated by GDP deflator

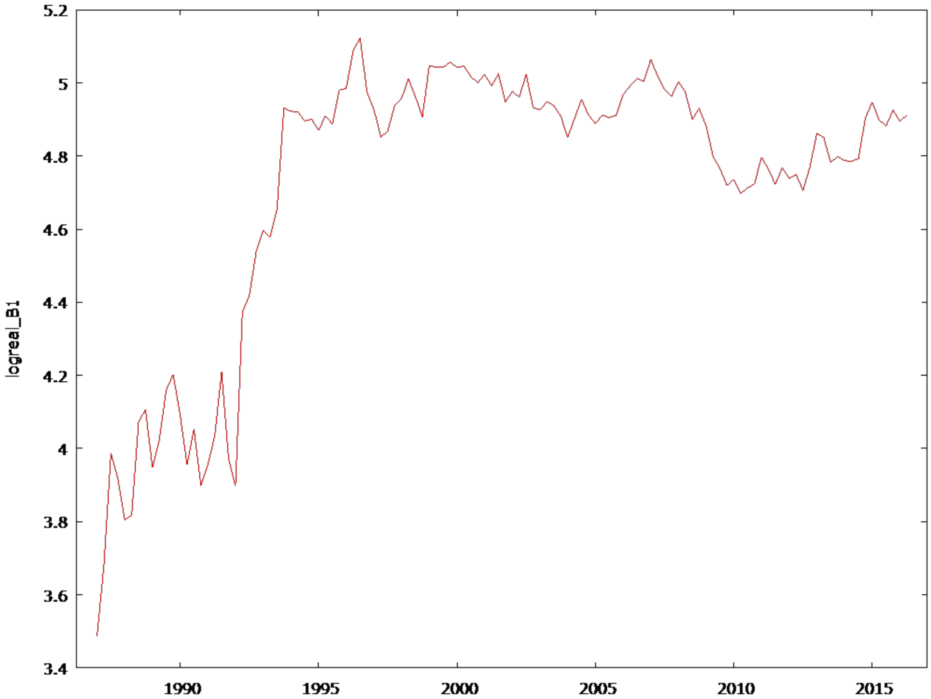


Figure A.15: M4 Securitisation ('M4 lending' minus 'M4 lending excluding intermediate OFCs')

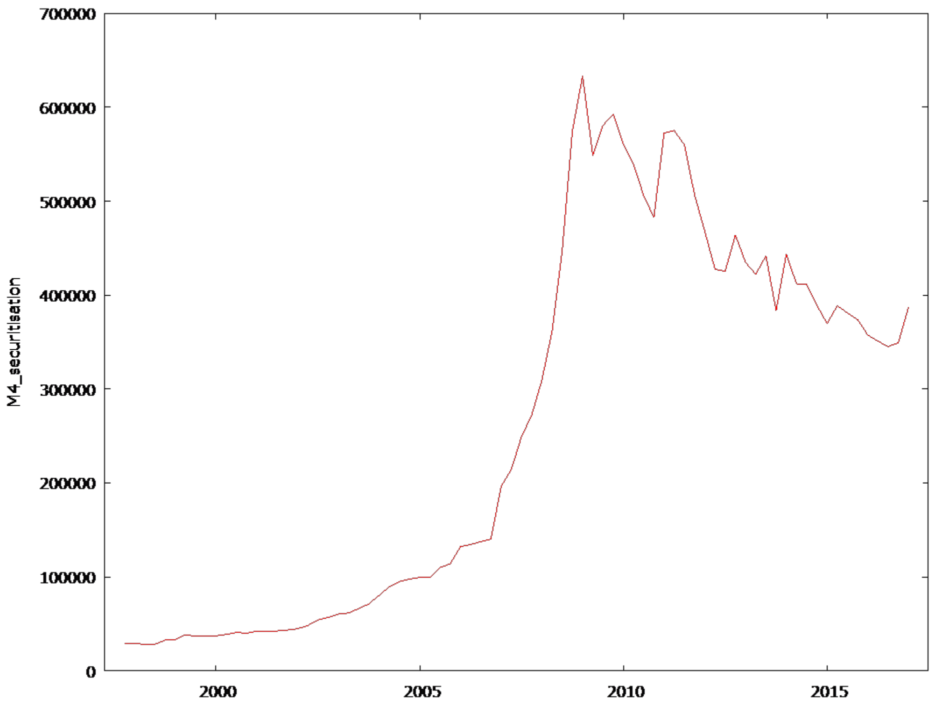


Figure A.16: l_realM4_securit (log of M4 Securitisation deflated by GDP deflator

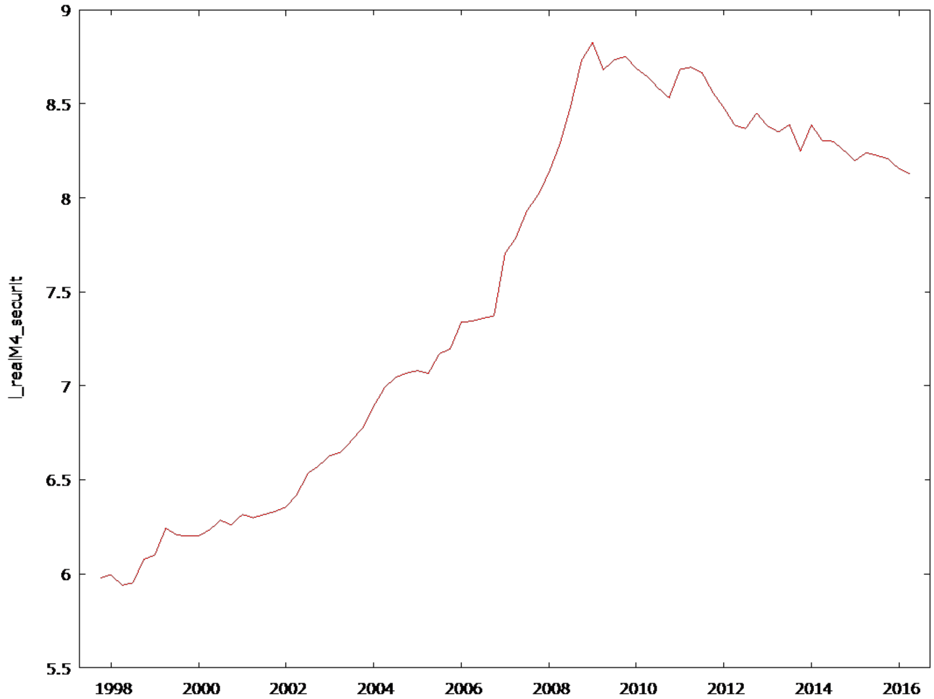
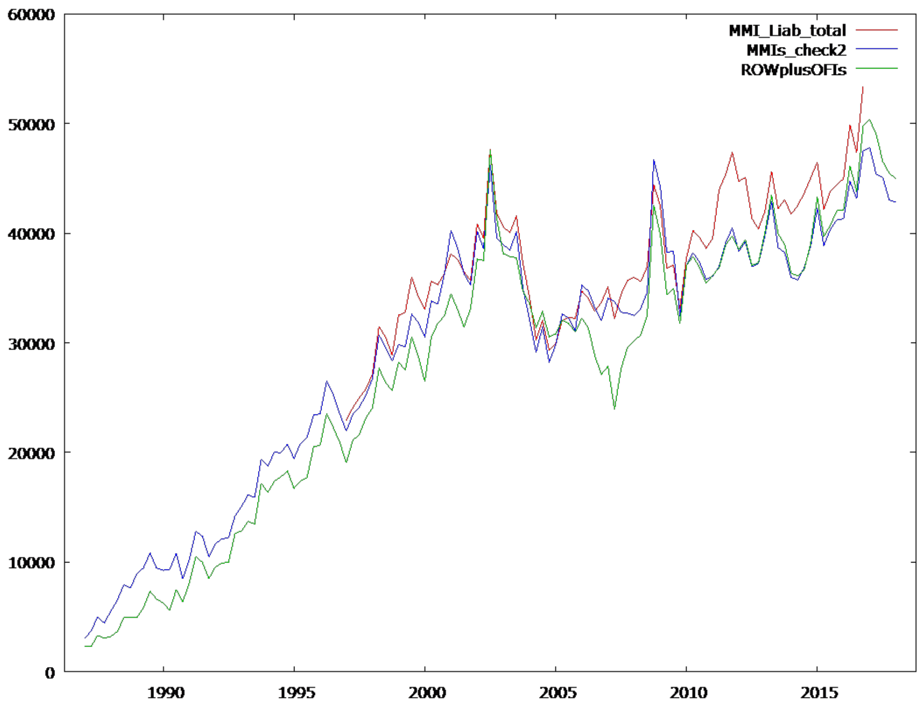


Figure A.17: Measures of Money Market Instruments



MMI_Liab_total (total economy, short-term debt securities issued, MMIs by other UK residents), MMIs_check2 (checksum of all-sector asset holdings of MMIs by other UK residents), ROWplusOFIs (checksum of RoW position in UK MMIs plus OFI sector net position

Mean dependent var	4.723014	S.D. dependent var	0.381452
Sum squared resid	7.295281	S.E. of regression	0.252970
R^2	0.571476	Adjusted R^2	0.560199
$F(3, 114)$	50.67643	P-value(F)	6.87e–21
Log-likelihood	−3.210790	Akaike criterion	14.42158
Schwarz criterion	25.50432	Hannan–Quinn	18.92150
$\hat{\rho}$	0.860419	Durbin–Watson	0.187877

B1b, log real B1 dependent, contemporaneous OLS with log real GDP, RPI, 10-year gilt yield, log real M4

B1b: OLS, using observations 1987:1–2016:2 (T = 118)
Dependent variable: logreal_B1

	Coefficient	Std. Error	t-ratio	p-value
const	−21.6101	6.12502	−3.528	0.0006
l_rgdp	2.63929	0.573044	4.606	0.0000
RPI	−0.0696629	0.0159645	−4.364	0.0000
ytm_10yrGilt	−0.00486824	0.0302186	−0.1611	0.8723
l_realM4	−0.755757	0.217539	−3.474	0.0007

Mean dependent var	4.723014	S.D. dependent var	0.381452
Sum squared resid	6.591269	S.E. of regression	0.241516
R^2	0.612829	Adjusted R^2	0.599124
$F(4, 113)$	44.71525	P-value(F)	1.85e–22
Log-likelihood	2.776636	Akaike criterion	4.446728
Schwarz criterion	18.30015	Hannan–Quinn	10.07163
$\hat{\rho}$	0.857588	Durbin–Watson	0.188092

B1c, log real B1 dependent, contemporaneous OLS with log real GDP, RPI, 10-year gilt yield, log real M4, log real M0

B1c: OLS, using observations 1987:1–2016:2 (T = 118)
Dependent variable: logreal_B1

	Coefficient	Std. Error	t-ratio	p-value
const	−35.8117	3.64701	−9.819	0.0000
l_rgdp	4.65155	0.355502	13.08	0.0000
RPI	−0.0391315	0.00940470	−4.161	0.0001
ytm_10yrGilt	−0.0874356	0.0182228	−4.798	0.0000
l_realM4	0.0554890	0.136155	0.4075	0.6844
l_realM0	−3.08743	0.203890	−15.14	0.0000

Mean dependent var	4.723014	S.D. dependent var	0.381452
Sum squared resid	2.162979	S.E. of regression	0.138969
R^2	0.872947	Adjusted R^2	0.867275
$F(5, 112)$	153.9041	P-value(F)	1.78e–48
Log-likelihood	68.51794	Akaike criterion	−125.0359
Schwarz criterion	−108.4118	Hannan–Quinn	−118.2860
$\hat{\rho}$	0.720019	Durbin–Watson	0.543468

Test for normality of residual –
Null hypothesis: error is normally distributed
Test statistic: $\chi^2(2) = 20.1092$
with p-value = 4.29865e-005

B1d, log real B1 dependent, contemporaneous OLS with log real GDP, RPI, 10-year gilt yield, log real M4, log real M0, ON_gilt_repo (overnight gilt repo rate)

B1d: OLS, using observations 1996:1–2016:2 ($T = 82$)
Dependent variable: logreal_B1

	Coefficient	Std. Error	t-ratio	p-value
const	−4.09477	4.34624	−0.9421	0.3491
l_rgdp	0.978479	0.525015	1.864	0.0663
RPI	−0.0178944	0.00542075	−3.301	0.0015
ytm_10yrGilt	0.00359471	0.0119117	0.3018	0.7637
l_realM4	−0.234658	0.0790249	−2.969	0.0040
l_realM0	−0.221615	0.396908	−0.5584	0.5783
ON_gilt_repo	0.0235946	0.0131353	1.796	0.0765

Mean dependent var	4.910360	S.D. dependent var	0.105133
Sum squared resid	0.239937	S.E. of regression	0.056561
R^2	0.732000	Adjusted R^2	0.710560
$F(6, 75)$	34.14187	P-value(F)	1.49e–19
Log-likelihood	122.8451	Akaike criterion	−231.6902
Schwarz criterion	−214.8432	Hannan–Quinn	−224.9264
$\hat{\rho}$	0.563276	Durbin–Watson	0.873827

Test for normality of residual –
Null hypothesis: error is normally distributed
Test statistic: $\chi^2(2) = 0.074737$
with p-value = 0.963321

Test for omission of variables –
Null hypothesis: parameters are zero for the variables
ytm_10yrGilt
Test statistic: $F(1, 75) = 0.0910706$
with p-value = $P(F(1, 75) > 0.0910706) = 0.763656$

B1e, log real B1 dependent, contemporaneous OLS with log real GDP, RPI, log real M4, ON_gilt_repo

B1e: OLS, using observations 1996:1–2016:2 ($T = 82$)
Dependent variable: logreal_B1

	Coefficient	Std. Error	t-ratio	p-value
const	−1.10176	1.36592	−0.8066	0.4224
l_rgdp	0.633515	0.146510	4.324	0.0000
RPI	−0.0179379	0.00537575	−3.337	0.0013
l_realM4	−0.229085	0.0743865	−3.080	0.0029
ON_gilt_repo	0.0325179	0.00574796	5.657	0.0000

Mean dependent var	4.910360	S.D. dependent var	0.105133
Sum squared resid	0.242284	S.E. of regression	0.056094
R^2	0.729378	Adjusted R^2	0.715320
$F(4, 77)$	51.88250	P-value(F)	4.07e–21
Log-likelihood	122.4459	Akaike criterion	−234.8918
Schwarz criterion	−222.8582	Hannan–Quinn	−230.0605
$\hat{\rho}$	0.564196	Durbin–Watson	0.870875

Test for normality of residual –
Null hypothesis: error is normally distributed
Test statistic: $\chi^2(2) = 0.129169$
with p-value = 0.937457

QLR test for structural break –
Null hypothesis: no structural break
Test statistic: max $\chi^2(5) = 36.0221$ (2006:1)
with asymptotic p-value = 3.33404e-005

B1f, VECM system on log real B1, log real GDP, RPI, log real M4, overnight repo rate

VAR lag selection for system B1f

Figure A.18: B1e, residuals time-series

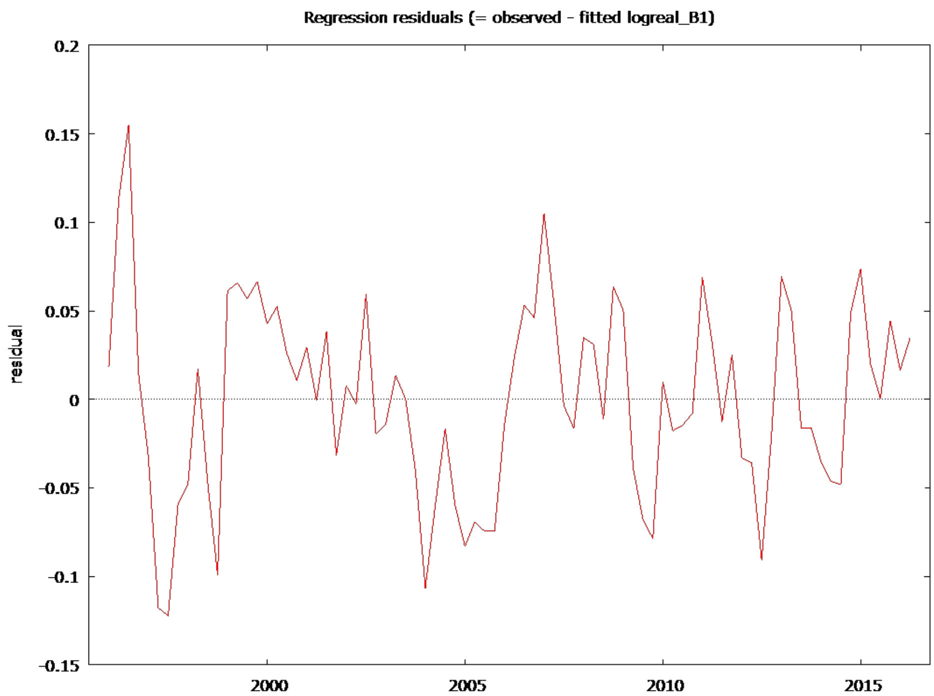


Table A.5: Information criteria for lag selection, system B1f

lags	loglik	p(LR)	AIC	BIC	HQC
1	562.48711		-14.391543	-13.457463	-14.018927
2	622.04804	0.00000	-15.325623	-13.613142*	-14.642493*
3	638.84084	0.11707	-15.103806	-12.612925	-14.110163
4	663.93843	0.00202	-15.106444	-11.837162	-13.802287
5	696.18373	0.00002	-15.302263	-11.254581	-13.687593
6	725.60603	0.00015	-15.421785	-10.595702	-13.496601
7	753.60175	0.00036	-15.502750	-9.898267	-13.267053
8	791.31382	0.00000	-15.846319*	-9.463436	-13.300109

Table A.6: Trace and maximum eigenvalue tests for system B1f

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.45382	124.86 [0.0000]	48.385 [0.0002]
1	0.41412	76.477 [0.0000]	42.771 [0.0001]
2	0.24089	33.706 [0.0160]	22.048 [0.0350]
3	0.11867	11.658 [0.1763]	10.106 [0.2090]
4	0.019211	1.5518 [0.2129]	1.5518 [0.2129]

Johansen rank selection for system B1f

Model B1f

VECM system, lag order 2

Maximum likelihood estimates, observations 1996:3–2016:2 ($T = 80$)

Cointegration rank = 3

Case 3: Unrestricted constant

Restrictions on beta: b[1,1] = -1 b[2,2] = -1 b[3,3] = -1

Cointegrating vectors

logreal_B1$_{t-1}$	1.00000	−0.502864	48.8954
l_rgdp$_{t-1}$	5.19998	1.00000	−17.4703
RPI$_{t-1}$	0.814023	−0.00153295	1.00000
l_realM4$_{t-1}$	−4.51823	−0.262809	3.58678
ON_gilt_repo$_{t-1}$	−0.509455	0.0418617	−1.24931

Adjustment vectors

logreal_B1$_{t-1}$	1.00000	−17.0425	0.176440
l_rgdp$_{t-1}$	−0.889697	1.00000	−0.00236186
RPI$_{t-1}$	−486.257	163.590	1.00000
l_realM4$_{t-1}$	−8.54742	−6.37799	−0.0448890
ON_gilt_repo$_{t-1}$	−49.8364	92.3759	0.0311784

Log-likelihood = 651.731

Determinant of covariance matrix = 0.00000

AIC = −14.9183

BIC = −13.2806

HQC = −14.2617

Equation 1: ΔlogreaI_B1

	Coefficient	Std. Error	t-ratio	p-value
const	−2.46729	0.666273	−3.703	0.0004
d_logreal_B1_1	0.136635	0.0998750	1.368	0.1754
d_l_rgdp_1	0.816191	0.864436	0.9442	0.3481
ΔRPI_{t-1}	0.0113690	0.00786313	1.446	0.1524
d_l_realM4_1	−0.992754	0.316112	−3.141	0.0024
d_ON_gilt_repo_1	−0.0303551	0.0173529	−1.749	0.0844
EC1	−0.000859652	0.00526468	−0.1633	0.8707
EC2	−0.338850	0.0805242	−4.208	0.0001
EC3	0.00564307	0.00156653	3.602	0.0006

Mean dependent var	−0.002191	S.D. dependent var	0.048483
Sum squared resid	0.114306	S.E. of regression	0.039302
R^2	0.384456	Adjusted R^2	0.342865
$\hat{\rho}$	−0.102060	Durbin–Watson	2.124484

Equation 2: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.179764	0.0796332	2.257	0.0269
d_logreal_B1_1	−0.00627500	0.0119371	−0.5257	0.6007
d_l_rgdp_1	0.644017	0.103318	6.233	0.0000
ΔRPI_{t-1}	−0.000651315	0.000939804	−0.6930	0.4905
d_l_realM4_1	0.00412171	0.0377819	0.1091	0.9134
d_ON_gilt_repo_1	0.00284878	0.00207402	1.374	0.1737
EC1	0.000764830	0.000629237	1.215	0.2280
EC2	0.0198827	0.00962429	2.066	0.0423
EC3	−7.55393e–005	0.000187233	−0.4035	0.6878

Mean dependent var	0.005112	S.D. dependent var	0.006219
Sum squared resid	0.001633	S.E. of regression	0.004697
R^2	0.465643	Adjusted R^2	0.429538
$\hat{\rho}$	−0.091770	Durbin–Watson	2.180684

Equation 3: ΔRPI

	Coefficient	Std. Error	t-ratio	p-value
const	39.6062	8.55896	4.627	0.0000
d_logreal_B1_1	0.549089	1.28300	0.4280	0.6699
d_l_rgdp_1	18.6588	11.1046	1.680	0.0971
ΔRPI_{t-1}	0.399824	0.101010	3.958	0.0002
d_l_realM4_1	−0.0761019	4.06079	−0.01874	0.9851
d_ON_gilt_repo_1	0.735537	0.222915	3.300	0.0015
EC1	0.418012	0.0676303	6.181	0.0000
EC2	3.25261	1.03442	3.144	0.0024
EC3	0.0319830	0.0201237	1.589	0.1163

Mean dependent var	−0.010000	S.D. dependent var	0.764331
Sum squared resid	18.86275	S.E. of regression	0.504878
R^2	0.591291	Adjusted R^2	0.563675
$\hat{\rho}$	−0.049408	Durbin–Watson	2.093142

Equation 4: Δl_realM4

	Coefficient	Std. Error	t-ratio	p-value
const	−0.857259	0.227154	−3.774	0.0003
d_logreal_B1_1	0.0107231	0.0340506	0.3149	0.7537
d_l_rgdp_1	−0.834473	0.294714	−2.831	0.0060
ΔRPI_{t-1}	0.0105163	0.00268079	3.923	0.0002
d_l_realM4_1	−0.189910	0.107773	−1.762	0.0822
d_ON_gilt_repo_1	−0.00426957	0.00591615	−0.7217	0.4728
EC1	0.00734781	0.00179490	4.094	0.0001
EC2	−0.126811	0.0274533	−4.619	0.0000
EC3	−0.00143568	0.000534082	−2.688	0.0089

Mean dependent var	0.010602	S.D. dependent var	0.017515
Sum squared resid	0.013286	S.E. of regression	0.013399
R^2	0.451757	Adjusted R^2	0.414714
$\hat{\rho}$	−0.083829	Durbin–Watson	2.156081

Equation 5: ΔON_gilt_repo

	Coefficient	Std. Error	t-ratio	p-value
const	15.8551	4.78435	3.314	0.0014
d_logreal_B1_1	0.146839	0.717180	0.2047	0.8383
d_l_rgdp_1	22.9627	6.20732	3.699	0.0004
$\Delta \mathrm{RPI}_{t-1}$	−0.0564972	0.0564634	−1.001	0.3203
d_l_realM4_1	0.850612	2.26993	0.3747	0.7089
d_ON_gilt_repo_1	0.633211	0.124607	5.082	0.0000
EC1	0.0428419	0.0378045	1.133	0.2608
EC2	1.83668	0.578226	3.176	0.0022
EC3	0.000997179	0.0112489	0.08865	0.9296

Mean dependent var	−0.067627	S.D. dependent var	0.404656
Sum squared resid	5.893994	S.E. of regression	0.282221
R^2	0.544373	Adjusted R^2	0.513587
$\hat{\rho}$	0.042980	Durbin–Watson	1.905166

A.2.3 B2, Models of log real M4 Securitisation

B2a, log real M4 securitisation dependent, contemporaneous OLS with log real gdp, RPI, log real M4, overnight gilt repo rate

B2a: OLS, using observations 1997:4–2016:2 ($T = 75$)
Dependent variable: l_realM4_securit

	Coefficient	Std. Error	t-ratio	p-value
const	−9.62668	3.11366	−3.092	0.0029
l_rgdp	−1.93684	0.315865	−6.132	0.0000
RPI	−0.0271704	0.0107663	−2.524	0.0139
l_realM4	4.33907	0.148678	29.18	0.0000
ON_gilt_repo	0.0384803	0.0116064	3.315	0.0015

Table A.7: Information criteria for lag selection, system B2b

lags	loglik	p(LR)	AIC	BIC	HQC
1	513.28286		-13.613602	-12.657540*	-13.233406
2	565.45155	0.00000	-14.378917*	-12.626137	-13.681892*
3	584.52736	0.04471	-14.212038	-11.662540	-13.198184
4	610.21068	0.00144	-14.231287	-10.885070	-12.900603
5	696.18373	0.00002	-15.302263	-11.254581	-13.687593
6	725.60603	0.00015	-15.421785	-10.595702	-13.496601
7	753.60175	0.00036	-15.502750	-9.898267	-13.267053
8	791.31382	0.00000	-15.846319*	-9.463436	-13.300109

Mean dependent var	7.494599	S.D. dependent var	0.981025
Sum squared resid	0.875338	S.E. of regression	0.111825
R^2	0.987709	Adjusted R^2	0.987007
$F(4, 70)$	1406.317	P-value(F)	4.86e–66
Log-likelihood	60.47837	Akaike criterion	−110.9567
Schwarz criterion	−99.36930	Hannan–Quinn	−106.3300
$\hat{\rho}$	0.714617	Durbin–Watson	0.565530

Test for omission of variables –

Null hypothesis: parameters are zero for the variables

l_realM4

Test statistic: $F(1, 70) = 851.723$

with p-value = $P(F(1, 70) > 851.723) = $ 6.48505e-041

B2b, VECM system on log real M4 securitisation, log real GDP, log real M4, RPI, overnight gilt repo rate

VAR lag selection for system B2b

Table A.8: Trace and maximum eigenvalue tests for system B2b

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.50388	126.19 [0.0000]	51.169 [0.0001]
1	0.45408	75.018 [0.0000]	44.186 [0.0001]
2	0.22649	30.832 [0.0375]	18.748 [0.1061]
3	0.11709	12.084 [0.1544]	9.0905 [0.2852]
4	0.040178	2.9936 [0.0836]	2.9936 [0.0836]

Johansen rank selection for system B2b

Model B2b

VECM system, lag order 2

Maximum likelihood estimates, observations 1998:2–2016:2 ($T = 73$)

Cointegration rank = 2

Case 3: Unrestricted constant

Restrictions on beta: b[1,1] = -1 b[2,5] = -1 b[1,4] = 0 b[2,3] = 0

Cointegrating vectors (standard errors in parentheses)

l_rgdp$_{t-1}$	-1.00000	-7.88366
	(0.00000)	(1.49453)
l_realM4$_{t-1}$	0.562120	4.66209
	(0.187578)	(0.667194)
RPI$_{t-1}$	-0.0404615	0.00000
	(0.00461929)	(0.00000)
ON_gilt_repo$_{t-1}$	0.00000	-0.322364
	(0.00000)	(0.0521174)
l_realM4_securit$_{t-1}$	-0.0556035	-1.00000
	(0.0541789)	(0.00000)

Adjustment vectors (standard errors in parentheses)

l_rgdp$_{t-1}$	0.0121671	0.00187216
	(0.0125080)	(0.00149121)
l_realM4$_{t-1}$	0.118876	-0.0251547
	(0.0316655)	(0.00377519)
RPI$_{t-1}$	9.02615	-0.305206
	(1.38320)	(0.164907)
ON_gilt_repo$_{t-1}$	0.735664	0.0695498
	(0.798845)	(0.0952391)
l_realM4_securit$_{t-1}$	0.0283297	-0.0890182
	(0.198576)	(0.0236744)

Log-likelihood = 562.599

Determinant of covariance matrix = 1.39171e–013

AIC = -13.9068

BIC = −12.1811

HQC = −13.2191

Equation 1: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.220111	0.0914881	2.406	0.0190
d_l_rgdp_1	0.662164	0.106890	6.195	0.0000
d_l_realM4_1	0.0781860	0.0450486	1.736	0.0874
$\Delta \mathrm{RPI}_{t-1}$	−0.00142475	0.000987911	−1.442	0.1541
d_ON_gilt_repo_1	0.00292868	0.00216363	1.354	0.1806
d_l_realM4_securit_1	−0.00566784	0.00858256	−0.6604	0.5114
EC1	0.0121671	0.0125080	0.9727	0.3343
EC2	0.00187216	0.00149121	1.255	0.2139

Mean dependent var	0.004856	S.D. dependent var	0.006380
Sum squared resid	0.001420	S.E. of regression	0.004710
R^2	0.515669	Adjusted R^2	0.455128
$\hat{\rho}$	−0.137351	Durbin–Watson	2.268273

Equation 2: Δl_realM4

	Coefficient	Std. Error	t-ratio	p-value
const	−0.673759	0.231613	−2.909	0.0050
d_l_rgdp_1	−0.341838	0.270606	−1.263	0.2111
d_l_realM4_1	−0.215833	0.114046	−1.893	0.0629
$\Delta \mathrm{RPI}_{t-1}$	0.0101124	0.00250102	4.043	0.0001
d_ON_gilt_repo_1	−0.00537574	0.00547749	−0.9814	0.3301
d_l_realM4_securit_1	0.0125172	0.0217278	0.5761	0.5666
EC1	0.118876	0.0316655	3.754	0.0004
EC2	−0.0251547	0.00377519	−6.663	0.0000

Mean dependent var	0.010170	S.D. dependent var	0.016620
Sum squared resid	0.009098	S.E. of regression	0.011923
R^2	0.542523	Adjusted R^2	0.485338
$\hat{\rho}$	−0.083548	Durbin–Watson	2.161971

Equation 3: ΔRPI

	Coefficient	Std. Error	t-ratio	p-value
const	52.1778	10.1173	5.157	0.0000
d_l_rgdp_1	15.5617	11.8205	1.317	0.1927
d_l_realM4_1	−2.66532	4.98172	−0.5350	0.5945
$\Delta\mathrm{RPI}_{t-1}$	0.391807	0.109249	3.586	0.0006
d_ON_gilt_repo_1	0.885337	0.239266	3.700	0.0004
d_l_realM4_securit_1	0.936560	0.949107	0.9868	0.3275
EC1	9.02615	1.38320	6.526	0.0000
EC2	−0.305206	0.164907	−1.851	0.0688

Mean dependent var	−0.027397	S.D. dependent var	0.789560
Sum squared resid	17.36029	S.E. of regression	0.520821
R^2	0.613229	Adjusted R^2	0.564883
$\hat{\rho}$	−0.057376	Durbin–Watson	2.097659

Equation 4: ΔON_gilt_repo

	Coefficient	Std. Error	t-ratio	p-value
const	10.2627	5.84305	1.756	0.0838
d_l_rgdp_1	18.8508	6.82674	2.761	0.0075
d_l_realM4_1	1.16471	2.87711	0.4048	0.6870
$\Delta\mathrm{RPI}_{t-1}$	−0.0481441	0.0630947	−0.7630	0.4482
d_ON_gilt_repo_1	0.567800	0.138184	4.109	0.0001
d_l_realM4_securit_1	−0.454505	0.548141	−0.8292	0.4101
EC1	0.735664	0.798845	0.9209	0.3606
EC2	0.0695498	0.0952391	0.7303	0.4679

Mean dependent var	−0.092126	S.D. dependent var	0.408442
Sum squared resid	5.790431	S.E. of regression	0.300791
R^2	0.517921	Adjusted R^2	0.457661
$\hat{\rho}$	0.102602	Durbin–Watson	1.793509

Equation 5: Δl_realM4_secu

	Coefficient	Std. Error	t-ratio	p-value
const	−5.51344	1.45246	−3.796	0.0003
d_l_rgdp_1	−2.27609	1.69698	−1.341	0.1846
d_l_realM4_1	−0.760797	0.715189	−1.064	0.2914
ΔRPI_{t-1}	0.0145751	0.0156840	0.9293	0.3562
d_ON_gilt_repo_1	−0.00456690	0.0343497	−0.1330	0.8946
d_l_realM4_securit_1	−0.0668258	0.136256	−0.4904	0.6255
EC1	0.0283297	0.198576	0.1427	0.8870
EC2	−0.0890182	0.0236744	−3.760	0.0004

Mean dependent var	0.029218	S.D. dependent var	0.085319
Sum squared resid	0.357799	S.E. of regression	0.074770
R^2	0.317318	Adjusted R^2	0.231983
$\hat{\rho}$	−0.017708	Durbin–Watson	1.989616

A.2.4 B3, Models of log real aggregate Monemy Market Instruments held by UK sectors (Rest of World excluded)

B3a, log real B3 dependent (aggreagate MMIs held by UK sectors), contemporaneous OLS with log real GDP, RPI, 10-year gilt yield, overnight gilt repo rate

Model 8: OLS, using observations 1996:1–2016:2 ($T = 82$)
Dependent variable: l_realB3

	Coefficient	Std. Error	t-ratio	p-value
const	10.9721	3.06417	3.581	0.0006
l_rgdp	−0.367171	0.233663	−1.571	0.1202
RPI	−0.0226267	0.0102548	−2.206	0.0303
ytm_10yrGilt	−0.0583795	0.0210940	−2.768	0.0071
ON_gilt_repo	0.0179871	0.0107146	1.679	0.0973

Table A.9: Information criteria for lag selection, system B3b

lags	loglik	p(LR)	AIC	BIC	HQC
1	535.26832		-12.980745	-11.692708*	-12.465983
2	601.65878	0.00000	-13.780494	-11.388426	-12.824508*
3	631.29112	0.00862	-13.612924	-10.116824	-12.215713
4	677.75191	0.00000	-13.888208	-9.288076	-12.049773
5	730.92782	0.00000	-14.340206*	-8.636043	-12.060546
6	766.42814	0.00045	-14.327056	-7.518862	-11.606172

Mean dependent var	5.989774	S.D. dependent var	0.126097
Sum squared resid	1.079577	S.E. of regression	0.118408
R^2	0.161773	Adjusted R^2	0.118229
$F(4, 77)$	3.715150	P-value(F)	0.008099
Log-likelihood	61.18320	Akaike criterion	−112.3664
Schwarz criterion	−100.3328	Hannan–Quinn	−107.5351
$\hat{\rho}$	0.758938	Durbin–Watson	0.469674

B3b, VECM system on log real B3, log real GDP, log real M4, RPI, 10-year gilt yield, overnight gilt repo rate

VAR lag selection for system B3b

Table A.10: Trace and maximum eigenvalue tests for system B3b

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.48061	140.29 [0.0000]	52.408 [0.0006]
1	0.38971	87.880 [0.0007]	39.506 [0.0069]
2	0.23605	48.374 [0.0430]	21.540 [0.2530]
3	0.16590	26.834 [0.1083]	14.512 [0.3378]
4	0.11116	12.321 [0.1432]	9.4270 [0.2579]

Johansen rank selection for system B3b

Model B3b

VECM system, lag order 2

Maximum likelihood estimates, observations 1996:3–2016:2 ($T = 80$)

Cointegration rank = 2

Case 3: Unrestricted constant

Restrictions on beta: b[1,1] = -1 b[2,5] = -1 b[1,4] = 0 b[2,3] = 0

Cointegrating vectors (standard errors in parentheses)

l_rgdp$_{t-1}$	-1.00000	4.76364
	(0.00000)	(1.54487)
l_realM4$_{t-1}$	0.661695	-1.40227
	(0.0978451)	(0.658874)
RPI$_{t-1}$	-0.0743605	0.00000
	(0.00962004)	(0.00000)
ON_gilt_repo$_{t-1}$	0.00000	0.208170
	(0.00000)	(0.0570393)
l_realB3$_{t-1}$	0.223743	-1.00000
	(0.104322)	(0.00000)
ytm_10yrGilt$_{t-1}$	0.0608575	-0.0862104
	(0.0192218)	(0.102157)

Adjustment vectors (standard errors in parentheses)

l_rgdp$_{t-1}$	0.00771335	-0.00109431
	(0.00655359)	(0.00169169)
l_realM4$_{t-1}$	0.0649795	0.0313673
	(0.0183302)	(0.00473160)
RPI$_{t-1}$	4.00654	0.157481
	(0.696519)	(0.179793)
ON_gilt_repo$_{t-1}$	0.498821	-0.121655
	(0.379584)	(0.0979825)
l_realB3$_{t-1}$	-0.132623	0.0414051
	(0.100908)	(0.0260475)
ytm_10yrGilt$_{t-1}$	0.0154528	0.0521443
	(0.392707)	(0.101370)

Log-likelihood = 607.104

Determinant of covariance matrix = 0.00000

AIC = −13.2276

BIC = −10.9051

HQC = −12.2965

Equation 1: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.0874665	0.0605917	1.444	0.1533
d_l_rgdp_1	0.656865	0.107526	6.109	0.0000
d_l_realM4_1	0.000445433	0.0399534	0.01115	0.9911
ΔRPI_{t-1}	−0.000787217	0.000989476	−0.7956	0.4290
d_ON_gilt_repo_1	0.00258064	0.00217468	1.187	0.2394
d_l_realB3_1	0.00404349	0.00738239	0.5477	0.5856
Δytm_{t-10}	0.000423920	0.00193229	0.2194	0.8270
EC1	0.00771335	0.00655359	1.177	0.2432
EC2	−0.00109431	0.00169169	−0.6469	0.5198

Mean dependent var	0.005112	S.D. dependent var	0.006219
Sum squared resid	0.001672	S.E. of regression	0.004887
R^2	0.452910	Adjusted R^2	0.382570
$\hat{\rho}$	−0.085262	Durbin–Watson	2.164297

Equation 2: Δl_realM4

	Coefficient	Std. Error	t-ratio	p-value
const	−0.975327	0.169473	−5.755	0.0000
d_l_rgdp_1	−0.769393	0.300748	−2.558	0.0127
d_l_realM4_1	−0.201419	0.111748	−1.802	0.0758
ΔRPI_{t-1}	0.0104060	0.00276753	3.760	0.0003
d_ON_gilt_repo_1	−0.00744568	0.00608251	−1.224	0.2250
d_l_realB3_1	0.00506154	0.0206483	0.2451	0.8071
Δytm_{t-10}	0.00267863	0.00540456	0.4956	0.6217
EC1	0.0649795	0.0183302	3.545	0.0007
EC2	0.0313673	0.00473160	6.629	0.0000

Mean dependent var	0.010602	S.D. dependent var	0.017515
Sum squared resid	0.013078	S.E. of regression	0.013669
R^2	0.460335	Adjusted R^2	0.390950
$\hat{\rho}$	−0.093842	Durbin–Watson	2.181085

Equation 3: ΔRPI

	Coefficient	Std. Error	t-ratio	p-value
const	13.7523	6.43971	2.136	0.0362
d_l_rgdp_1	20.7261	11.4280	1.814	0.0740
d_l_realM4_1	−2.04952	4.24626	−0.4827	0.6308
ΔRPI_{t-1}	0.355752	0.105162	3.383	0.0012
d_ON_gilt_repo_1	0.665037	0.231126	2.877	0.0053
d_l_realB3_1	−1.20758	0.784604	−1.539	0.1283
Δytm_{t-10}	0.0207714	0.205365	0.1011	0.9197
EC1	4.00654	0.696519	5.752	0.0000
EC2	0.157481	0.179793	0.8759	0.3841

Mean dependent var	−0.010000	S.D. dependent var	0.764331
Sum squared resid	18.88364	S.E. of regression	0.519390
R^2	0.590838	Adjusted R^2	0.538232
$\hat{\rho}$	−0.098699	Durbin–Watson	2.194768

Equation 4: ΔON_gilt_repo

	Coefficient	Std. Error	t-ratio	p-value
const	7.55162	3.50947	2.152	0.0349
d_l_rgdp_1	22.4503	6.22792	3.605	0.0006
d_l_realM4_1	0.0187311	2.31410	0.008094	0.9936
ΔRPI_{t-1}	−0.0746235	0.0573105	−1.302	0.1972
d_ON_gilt_repo_1	0.580518	0.125957	4.609	0.0000
d_l_realB3_1	−0.249672	0.427588	−0.5839	0.5612
Δytm_{t-10}	0.236660	0.111918	2.115	0.0380
EC1	0.498821	0.379584	1.314	0.1931
EC2	−0.121655	0.0979825	−1.242	0.2185

Mean dependent var	−0.067627	S.D. dependent var	0.404656
Sum squared resid	5.608356	S.E. of regression	0.283054
R^2	0.566454	Adjusted R^2	0.510712
$\hat{\rho}$	0.016497	Durbin–Watson	1.955576

Equation 5: Δl_realB3

	Coefficient	Std. Error	t-ratio	p-value
const	−2.40053	0.932952	−2.573	0.0122
d_l_rgdp_1	−3.01586	1.65562	−1.822	0.0728
d_l_realM4_1	−0.617211	0.615176	−1.003	0.3192
ΔRPI_{t-1}	0.0379102	0.0152353	2.488	0.0152
d_ON_gilt_repo_1	−0.0356932	0.0334843	−1.066	0.2901
d_l_realB3_1	−0.164558	0.113669	−1.448	0.1522
Δytm_{t-10}	0.00154396	0.0297522	0.05189	0.9588
EC1	−0.132623	0.100908	−1.314	0.1930
EC2	0.0414051	0.0260475	1.590	0.1164

Mean dependent var	0.001984	S.D. dependent var	0.079093
Sum squared resid	0.396343	S.E. of regression	0.075247
R^2	0.198016	Adjusted R^2	0.094904
$\hat{\rho}$	−0.062699	Durbin–Watson	2.120615

Equation 6: Δytm_10yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	−2.22292	3.63079	−0.6122	0.5424
d_l_rgdp_1	9.56734	6.44323	1.485	0.1421
d_l_realM4_1	−2.32396	2.39410	−0.9707	0.3350
ΔRPI_{t-1}	0.0130531	0.0592917	0.2202	0.8264
d_ON_gilt_repo_1	−0.288074	0.130312	−2.211	0.0303
d_l_realB3_1	−0.284739	0.442370	−0.6437	0.5219
Δytm_{t-10}	0.305928	0.115787	2.642	0.0102
EC1	0.0154528	0.392707	0.03935	0.9687
EC2	0.0521443	0.101370	0.5144	0.6086

Table A.11: Information criteria for lag selection, system B4a

lags	loglik	p(LR)	AIC	BIC	HQC
1	572.73602		-18.301242	-16.809197*	-17.720061
2	635.77201	0.00000	-19.233517	-16.462577	-18.154180
3	658.90749	0.11735	-18.789914	-14.740077	-17.212421
4	710.14888	0.00000	-19.315478	-13.986747	-17.239830
5	751.21150	0.00002	-19.490052	-12.882424	-16.916247
6	808.61067	0.00000	-20.227954	-12.341431	-17.155994
7	877.07155	0.00000	-21.347295	-12.181876	-17.777179
8	1020.07189	0.00000	-25.036962*	-14.592647	-20.968690*

Mean dependent var	-0.082487	S.D. dependent var	0.302689
Sum squared resid	6.002831	S.E. of regression	0.292839
R^2	0.170652	Adjusted R^2	0.064021
$\hat{\rho}$	-0.005071	Durbin–Watson	2.002234

A.2.5 B4, Models of log real M4 Securitisation incorporating measures of government debt issuance

B4a, VECM system on log real M4 securitisation, log real GDP, log GDP deflator, 1 month LIBOR, 20-year gilt yield, log real short-term debt outstanding as a liability of central government (lr_STDebt_CG)

VAR lag selection for system B4a

Table A.12: Trace and maximum eigenvalue tests for system B4a

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.50305	127.77 [0.0000]	44.753 [0.0105]
1	0.44398	83.012 [0.0025]	37.565 [0.0138]
2	0.28208	45.447 [0.0815]	21.210 [0.2727]
3	0.20383	24.237 [0.1968]	14.588 [0.3319]
4	0.13133	9.6488 [0.3144]	9.0108 [0.2919]
5	0.0099201	0.63806 [0.4244]	0.63806 [0.4244]

Johansen rank selection for system B4a

Model B4a

VECM system, lag order 2

Maximum likelihood estimates, observations 2000:3–2016:2 ($T = 64$)

Cointegration rank = 1

Case 3: Unrestricted constant

Cointegrating vectors (standard errors in parentheses)

lr_M4_sec$_{t-1}$	1.00000
	(0.00000)
l_gdpdef$_{t-1}$	18.4302
	(7.18518)
l_rgdp$_{t-1}$	−42.5662
	(8.83466)
LIBOR_1m$_{t-1}$	0.913443
	(0.231148)
ytm_20yrGilt$_{t-1}$	−2.03626
	(0.303748)
lr_STDebt_CG$_{t-1}$	1.32729
	(0.423698)

Adjustment vectors

lr_M4_sec$_{t-1}$	1.00000
l_gdpdef$_{t-1}$	0.0254281
l_rgdp$_{t-1}$	0.00843449
LIBOR_1m$_{t-1}$	0.996402
ytm_20yrGilt$_{t-1}$	−1.01457
lr_STDebt_CG$_{t-1}$	3.76863

Log-likelihood = 618.281

Determinant of covariance matrix = 0.00000

AIC = −16.8838

BIC = −14.2526

HQC = −15.8472

Equation 1: Δlr_M4_sec

	Coefficient	Std. Error	t-ratio	p-value
const	−18.1476	5.51408	−3.291	0.0017
d_lr_M4_sec_1	0.0460085	0.128565	0.3579	0.7218
d_l_gdpdef_1	3.80414	2.16813	1.755	0.0848
d_l_rgdp_1	−6.06143	2.04716	−2.961	0.0045
ΔLIBOR_{t-1}	0.0735219	0.0282886	2.599	0.0119
Δytm_{t-20}	−0.0369230	0.0475793	−0.7760	0.4410
d_lr_STDebt_CG_1	0.0226388	0.0357992	0.6324	0.5297
EC1	−0.0397359	0.0120540	−3.297	0.0017

Mean dependent var	0.029617	S.D. dependent var	0.088053
Sum squared resid	0.323168	S.E. of regression	0.075966
R^2	0.338393	Adjusted R^2	0.255693
$\hat{\rho}$	−0.014158	Durbin–Watson	2.004873

Equation 2: Δl_gdpdef

	Coefficient	Std. Error	t-ratio	p-value
const	−0.456157	0.351723	−1.297	0.2000
d_lr_M4_sec_1	0.000207723	0.00820072	0.02533	0.9799
d_l_gdpdef_1	−0.200038	0.138297	−1.446	0.1536
d_l_rgdp_1	−0.112187	0.130581	−0.8591	0.3939
ΔLIBOR_{t-1}	0.00251757	0.00180443	1.395	0.1685
Δytm_{t-20}	−0.00277472	0.00303491	−0.9143	0.3645
d_lr_STDebt_CG_1	0.000462693	0.00228350	0.2026	0.8402
EC1	−0.00101041	0.000768878	−1.314	0.1942

Mean dependent var	0.004801	S.D. dependent var	0.004818
Sum squared resid	0.001315	S.E. of regression	0.004846
R^2	0.100816	Adjusted R^2	-0.011582
$\hat{\rho}$	−0.072317	Durbin–Watson	2.132418

Equation 3: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	−0.150985	0.334307	−0.4516	0.6533
d_lr_M4_sec_1	−0.0148048	0.00779466	−1.899	0.0627
d_l_gdpdef_1	−0.122525	0.131450	−0.9321	0.3553
d_l_rgdp_1	0.665573	0.124115	5.363	0.0000
ΔLIBOR$_{t-1}$	−0.00141186	0.00171508	−0.8232	0.4139
Δytm$_{t-20}$	0.000124877	0.00288463	0.04329	0.9656
d_lr_STDebt_CG_1	−0.00166231	0.00217043	−0.7659	0.4470
EC1	−0.000335152	0.000730807	−0.4586	0.6483

Mean dependent var	0.004298	S.D. dependent var	0.006389
Sum squared resid	0.001188	S.E. of regression	0.004606
R^2	0.538038	Adjusted R^2	0.480293
$\hat{\rho}$	−0.045868	Durbin–Watson	2.082137

Equation 4: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	−18.2512	23.0342	−0.7924	0.4315
d_lr_M4_sec_1	−0.991448	0.537062	−1.846	0.0702
d_l_gdpdef_1	−1.14968	9.05704	−0.1269	0.8994
d_l_rgdp_1	25.7704	8.55171	3.013	0.0039
ΔLIBOR$_{t-1}$	0.288446	0.118171	2.441	0.0178
Δytm$_{t-20}$	0.224451	0.198755	1.129	0.2636
d_lr_STDebt_CG_1	0.00856753	0.149546	0.05729	0.9545
EC1	−0.0395929	0.0503535	−0.7863	0.4350

Mean dependent var	−0.086511	S.D. dependent var	0.429329
Sum squared resid	5.639346	S.E. of regression	0.317337
R^2	0.514368	Adjusted R^2	0.453664
$\hat{\rho}$	0.042832	Durbin–Watson	1.913858

Equation 5: Δytm_20yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	18.3308	16.7326	1.096	0.2780
d_lr_M4_sec_1	0.616649	0.390136	1.581	0.1196
d_l_gdpdef_1	1.17052	6.57927	0.1779	0.8594
d_l_rgdp_1	12.2907	6.21218	1.978	0.0528
ΔLIBOR$_{t-1}$	−0.162457	0.0858427	−1.892	0.0636
Δytm$_{t-20}$	0.131227	0.144381	0.9089	0.3673
d_lr_STDebt_CG_1	−0.0952677	0.108634	−0.8770	0.3843
EC1	0.0403149	0.0365781	1.102	0.2751

Mean dependent var	−0.039531	S.D. dependent var	0.231049
Sum squared resid	2.975852	S.E. of regression	0.230522
R^2	0.115165	Adjusted R^2	0.004561
$\hat{\rho}$	0.005530	Durbin–Watson	1.986342

Equation 6: Δlr_STDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	−68.3671	15.3982	−4.440	0.0000
d_lr_M4_sec_1	−0.123071	0.359023	−0.3428	0.7330
d_l_gdpdef_1	−12.8274	6.05459	−2.119	0.0386
d_l_rgdp_1	−15.7139	5.71677	−2.749	0.0080
ΔLIBOR$_{t-1}$	−0.0924954	0.0789968	−1.171	0.2466
Δytm$_{t-20}$	−0.233112	0.132867	−1.754	0.0848
d_lr_STDebt_CG_1	−0.438035	0.0999705	−4.382	0.0001
EC1	−0.149750	0.0336611	−4.449	0.0000

Mean dependent var	0.042230	S.D. dependent var	0.279060
Sum squared resid	2.520139	S.E. of regression	0.212138
R^2	0.486325	Adjusted R^2	0.422115
$\hat{\rho}$	0.051234	Durbin–Watson	1.832908

B4b, VECM system of same composition as B4a but with 2 cointegrating vectors

VECM system, lag order 2

Maximum likelihood estimates, observations 2000:3–2016:2 ($T = 64$)

Cointegration rank = 2
Case 3: Unrestricted constant

Cointegrating vectors (standard errors in parentheses)

lr_M4_sec$_{t-1}$	1.00000	0.00000
	(0.00000)	(0.00000)
l_gdpdef$_{t-1}$	0.00000	1.00000
	(0.00000)	(0.00000)
l_rgdp$_{t-1}$	−16.2657	−1.42704
	(2.13017)	(0.0919944)
LIBOR_1m$_{t-1}$	0.295563	0.0335255
	(0.0808181)	(0.00349024)
ytm_20yrGilt$_{t-1}$	−1.29042	−0.0404684
	(0.175691)	(0.00758744)
lr_STDebt_CG$_{t-1}$	0.327062	0.0542711
	(0.219380)	(0.00947423)

Adjustment vectors

lr_M4_sec$_{t-1}$	1.00000	86.8952
l_gdpdef$_{t-1}$	0.0193173	1.00000
l_rgdp$_{t-1}$	0.0189507	2.81449
LIBOR_1m$_{t-1}$	−0.625030	−234.363
ytm_20yrGilt$_{t-1}$	−2.44386	−371.075
lr_STDebt_CG$_{t-1}$	−1.76134	−767.126

Log-likelihood = 637.063

Determinant of covariance matrix = 0.00000

AIC = −17.4707

BIC = −14.8396

HQC = −16.4342

Equation 1: Δlr_M4_sec

	Coefficient	Std. Error	t-ratio	p-value
const	−7.91907	7.28644	−1.087	0.2819
d_lr_M4_sec_1	−0.0248176	0.130400	−0.1903	0.8498
d_l_gdpdef_1	1.57474	2.37617	0.6627	0.5103
d_l_rgdp_1	−4.32766	2.16975	−1.995	0.0512
ΔLIBOR$_{t-1}$	0.0390856	0.0322315	1.213	0.2305
Δytm$_{t-20}$	−0.0237123	0.0470282	−0.5042	0.6162
d_lr_STDebt_CG_1	−0.00942618	0.0382698	−0.2463	0.8064
EC1	−0.126167	0.0429833	−2.935	0.0049
EC2	1.30660	0.998976	1.308	0.1964

Mean dependent var	0.029617	S.D. dependent var	0.088053
Sum squared resid	0.298956	S.E. of regression	0.074406
R^2	0.387960	Adjusted R^2	0.285954
$\hat{\rho}$	0.026272	Durbin–Watson	1.937936

Equation 2: Δl_gdpdef

	Coefficient	Std. Error	t-ratio	p-value
const	−0.287305	0.482016	−0.5960	0.5536
d_lr_M4_sec_1	−0.000961466	0.00862626	−0.1115	0.9117
d_l_gdpdef_1	−0.236840	0.157189	−1.507	0.1377
d_l_rgdp_1	−0.0835662	0.143534	−0.5822	0.5629
ΔLIBOR$_{t-1}$	0.00194910	0.00213219	0.9141	0.3647
Δytm$_{t-20}$	−0.00255664	0.00311103	−0.8218	0.4148
d_lr_STDebt_CG_1	−6.66313e–005	0.00253164	−0.02632	0.9791
EC1	−0.00243720	0.00284345	−0.8571	0.3952
EC2	0.0150365	0.0660847	0.2275	0.8209

Mean dependent var	0.004801	S.D. dependent var	0.004818
Sum squared resid	0.001308	S.E. of regression	0.004922
R^2	0.105328	Adjusted R^2	-0.043784
$\hat{\rho}$	−0.079554	Durbin–Watson	2.144768

Equation 3: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.0923059	0.456646	0.2021	0.8406
d_lr_M4_sec_1	−0.0164894	0.00817224	−2.018	0.0486
d_l_gdpdef_1	−0.175552	0.148916	−1.179	0.2436
d_l_rgdp_1	0.706811	0.135980	5.198	0.0000
ΔLIBOR_{t-1}	−0.00223094	0.00201997	−1.104	0.2743
Δytm_{t-20}	0.000439098	0.00294729	0.1490	0.8821
d_lr_STDebt_CG_1	−0.00242499	0.00239840	−1.011	0.3165
EC1	−0.00239095	0.00269379	−0.8876	0.3787
EC2	0.0423200	0.0626065	0.6760	0.5019

Mean dependent var	0.004298	S.D. dependent var	0.006389
Sum squared resid	0.001174	S.E. of regression	0.004663
R^2	0.543365	Adjusted R^2	0.467259
$\hat{\rho}$	−0.083899	Durbin–Watson	2.152638

Equation 4: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	−32.2691	31.5187	−1.024	0.3105
d_lr_M4_sec_1	−0.894383	0.564065	−1.586	0.1187
d_l_gdpdef_1	1.90564	10.2785	0.1854	0.8536
d_l_rgdp_1	23.3943	9.38562	2.493	0.0158
ΔLIBOR_{t-1}	0.335640	0.139423	2.407	0.0195
Δytm_{t-20}	0.206346	0.203428	1.014	0.3149
d_lr_STDebt_CG_1	0.0525116	0.165542	0.3172	0.7523
EC1	0.0788580	0.185931	0.4241	0.6732
EC2	−3.52400	4.32123	−0.8155	0.4184

Mean dependent var	−0.086511	S.D. dependent var	0.429329
Sum squared resid	5.593872	S.E. of regression	0.321854
R^2	0.518284	Adjusted R^2	0.437998
$\hat{\rho}$	0.059696	Durbin–Watson	1.880523

Equation 5: Δytm_20yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	−13.3876	22.0713	−0.6066	0.5467
d_lr_M4_sec_1	0.836279	0.394992	2.117	0.0389
d_l_gdpdef_1	8.08382	7.19763	1.123	0.2664
d_l_rgdp_1	6.91436	6.57237	1.052	0.2975
ΔLIBOR$_{t-1}$	−0.0556708	0.0976320	−0.5702	0.5709
Δytm$_{t-20}$	0.0902613	0.142453	0.6336	0.5290
d_lr_STDebt_CG_1	0.00416484	0.115923	0.03593	0.9715
EC1	0.308335	0.130200	2.368	0.0215
EC2	−5.57967	3.02598	−1.844	0.0707

Mean dependent var	−0.039531	S.D. dependent var	0.231049
Sum squared resid	2.743034	S.E. of regression	0.225382
R^2	0.184391	Adjusted R^2	0.048456
$\hat{\rho}$	−0.008104	Durbin–Watson	2.002871

Equation 6: Δlr_STDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	−112.388	19.1812	−5.859	0.0000
d_lr_M4_sec_1	0.181744	0.343270	0.5294	0.5987
d_l_gdpdef_1	−3.23273	6.25514	−0.5168	0.6074
d_l_rgdp_1	−23.1755	5.71176	−4.058	0.0002
ΔLIBOR$_{t-1}$	0.0557081	0.0848477	0.6566	0.5142
Δytm$_{t-20}$	−0.289967	0.123799	−2.342	0.0229
d_lr_STDebt_CG_1	−0.300037	0.100743	−2.978	0.0043
EC1	0.222223	0.113151	1.964	0.0547
EC2	−11.5349	2.62975	−4.386	0.0001

Mean dependent var	0.042230	S.D. dependent var	0.279060
Sum squared resid	2.071698	S.E. of regression	0.195869
R^2	0.577729	Adjusted R^2	0.507351
$\hat{\rho}$	0.052040	Durbin–Watson	1.845851

Table A.13: Information criteria for lag selection, system B4c

lags	loglik	p(LR)	AIC	BIC	HQC
1	688.74210		-22.301452	-20.809407*	-21.720270
2	750.51850	0.00000	-23.190293	-20.419353	-22.110956
3	772.44240	0.17298	-22.704910	-18.655074	-21.127417
4	815.94646	0.00000	-22.963671	-17.634939	-20.888022
5	853.06818	0.00018	-23.002351	-16.394723	-20.428547
6	902.99944	0.00000	-23.482739	-15.596216	-20.410779
7	997.52633	0.00000	-25.500908	-16.335489	-21.930792
8	1140.69366	0.00000	-29.196333*	-18.752019	-25.128062*

B4c, VECM system on log real M4 securitisation, log real GDP, log GDP deflator, 1 month LIBOR, 20-year gilt yield, log real long-term debt outstanding as a liability of central government (lr_LTDebt_CG)

VAR lag selection for system B4c

Table A.14: Trace and maximum eigenvalue tests for system B4c

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.55933	134.33 [0.0000]	52.446 [0.0006]
1	0.46505	81.887 [0.0033]	40.037 [0.0057]
2	0.27433	41.850 [0.1637]	20.523 [0.3167]
3	0.18427	21.327 [0.3478]	13.035 [0.4634]
4	0.11778	8.2924 [0.4419]	8.0204 [0.3851]
5	0.0042411	0.27201 [0.6020]	0.27201 [0.6020]

Johansen rank selection for system B4c

Model B4c

VECM system, lag order 2

Maximum likelihood estimates, observations 2000:3–2016:2 ($T = 64$)

Cointegration rank = 1

Case 3: Unrestricted constant

Cointegrating vectors (standard errors in parentheses)

lr_M4_sec$_{t-1}$	1.00000
	(0.00000)
l_gdpdef$_{t-1}$	7.08442
	(9.45041)
l_rgdp$_{t-1}$	4.22303
	(6.60968)
LIBOR_1m$_{t-1}$	−0.275945
	(0.0908059)
ytm_20yrGilt$_{t-1}$	−0.476773
	(0.336862)
lr_LTDebt_CG$_{t-1}$	−4.97299
	(1.30576)

Adjustment vectors

lr_M4_sec$_{t-1}$	1.00000
l_gdpdef$_{t-1}$	0.0652256
l_rgdp$_{t-1}$	−0.000332372
LIBOR_1m$_{t-1}$	5.32455
ytm_20yrGilt$_{t-1}$	2.46620
lr_LTDebt_CG$_{t-1}$	0.344324

Log-likelihood = 768.848

Determinant of covariance matrix = 0.00000

AIC = −21.5890

BIC = −18.9578

HQC = −20.5524

Equation 1: Δlr_M4_sec

	Coefficient	Std. Error	t-ratio	p-value
const	−2.00446	0.789937	−2.537	0.0140
d_lr_M4_sec_1	0.0739946	0.130218	0.5682	0.5721
d_l_gdpdef_1	1.19717	2.27015	0.5274	0.6000
d_l_rgdp_1	−4.36920	2.08716	−2.093	0.0409
ΔLIBOR_{t-1}	0.0906192	0.0292215	3.101	0.0030
Δytm_{t-20}	−0.0370122	0.0508369	−0.7281	0.4696
d_lr_LTDebt_CG_1	−0.971803	0.398453	−2.439	0.0179
EC1	0.0439350	0.0169128	2.598	0.0120

Mean dependent var	0.029617	S.D. dependent var	0.088053
Sum squared resid	0.336250	S.E. of regression	0.077488
R^2	0.311611	Adjusted R^2	0.225562
$\hat{\rho}$	−0.069477	Durbin–Watson	2.114181

Equation 2: Δl_gdpdef

	Coefficient	Std. Error	t-ratio	p-value
const	−0.126828	0.0462350	−2.743	0.0082
d_lr_M4_sec_1	−0.00431565	0.00762164	−0.5662	0.5735
d_l_gdpdef_1	−0.334123	0.132872	−2.515	0.0148
d_l_rgdp_1	−0.0997837	0.122161	−0.8168	0.4175
ΔLIBOR_{t-1}	0.00389165	0.00171033	2.275	0.0267
Δytm_{t-20}	−0.00472842	0.00297548	−1.589	0.1177
d_lr_LTDebt_CG_1	−0.0565541	0.0233214	−2.425	0.0186
EC1	0.00286569	0.000989903	2.895	0.0054

Mean dependent var	0.004801	S.D. dependent var	0.004818
Sum squared resid	0.001152	S.E. of regression	0.004535
R^2	0.212261	Adjusted R^2	0.113794
$\hat{\rho}$	−0.140016	Durbin–Watson	2.226542

Equation 3: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.00337533	0.0471950	0.07152	0.9432
d_lr_M4_sec_1	−0.0136789	0.00777989	−1.758	0.0842
d_l_gdpdef_1	−0.145433	0.135631	−1.072	0.2882
d_l_rgdp_1	0.660620	0.124698	5.298	0.0000
ΔLIBOR$_{t-1}$	−0.000956276	0.00174585	−0.5477	0.5860
Δytm$_{t-20}$	0.000185003	0.00303726	0.06091	0.9516
d_lr_LTDebt_CG_1	−0.00918843	0.0238056	−0.3860	0.7010
EC1	−1.46028e–005	0.00101046	−0.01445	0.9885

Mean dependent var	0.004298	S.D. dependent var	0.006389
Sum squared resid	0.001200	S.E. of regression	0.004630
R^2	0.533233	Adjusted R^2	0.474887
$\hat{\rho}$	−0.047206	Durbin–Watson	2.082800

Equation 4: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	−10.9847	2.83406	−3.876	0.0003
d_lr_M4_sec_1	−1.53908	0.467183	−3.294	0.0017
d_l_gdpdef_1	−11.3059	8.14463	−1.388	0.1706
d_l_rgdp_1	23.5613	7.48811	3.146	0.0026
ΔLIBOR$_{t-1}$	0.411715	0.104838	3.927	0.0002
Δytm$_{t-20}$	−0.00172128	0.182388	−0.009437	0.9925
d_lr_LTDebt_CG_1	−4.66061	1.42953	−3.260	0.0019
EC1	0.233934	0.0606780	3.855	0.0003

Mean dependent var	−0.086511	S.D. dependent var	0.429329
Sum squared resid	4.328080	S.E. of regression	0.278006
R^2	0.627288	Adjusted R^2	0.580698
$\hat{\rho}$	−0.010812	Durbin–Watson	1.987719

Equation 5: Δytm_20yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	−5.03091	1.98654	−2.532	0.0142
d_lr_M4_sec_1	0.0424648	0.327473	0.1297	0.8973
d_l_gdpdef_1	−4.92092	5.70899	−0.8620	0.3924
d_l_rgdp_1	−0.171134	5.24881	−0.03260	0.9741
ΔLIBOR_{t-1}	−0.0323812	0.0734866	−0.4406	0.6612
Δytm_{t-20}	−0.231707	0.127845	−1.812	0.0753
d_lr_LTDebt_CG_1	−5.02145	1.00203	−5.011	0.0000
EC1	0.108353	0.0425324	2.548	0.0136

Mean dependent var	−0.039531	S.D. dependent var	0.231049
Sum squared resid	2.126534	S.E. of regression	0.194869
R^2	0.367700	Adjusted R^2	0.288662
$\hat{\rho}$	0.031984	Durbin–Watson	1.892125

Equation 6: Δlr_LTDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	−0.694289	0.304165	−2.283	0.0263
d_lr_M4_sec_1	−0.0519608	0.0501403	−1.036	0.3045
d_l_gdpdef_1	0.909087	0.874119	1.040	0.3028
d_l_rgdp_1	−1.08964	0.803658	−1.356	0.1806
ΔLIBOR_{t-1}	0.00580074	0.0112517	0.5155	0.6082
Δytm_{t-20}	0.0273707	0.0195747	1.398	0.1675
d_lr_LTDebt_CG_1	0.315834	0.153424	2.059	0.0442
EC1	0.0151279	0.00651225	2.323	0.0238

Mean dependent var	0.022390	S.D. dependent var	0.034964
Sum squared resid	0.049853	S.E. of regression	0.029837
R^2	0.352675	Adjusted R^2	0.271760
$\hat{\rho}$	0.002627	Durbin–Watson	1.918330

B4d, VECM system of same composition as B4c but with 2 cointegrating vectors

VECM system, lag order 2

Maximum likelihood estimates, observations 2000:3–2016:2 ($T = 64$)

Cointegration rank = 2

Case 3: Unrestricted constant

Cointegrating vectors (standard errors in parentheses)

lr_M4_sec$_{t-1}$	1.00000	0.00000
	(0.00000)	(0.00000)
l_gdpdef$_{t-1}$	0.00000	1.00000
	(0.00000)	(0.00000)
l_rgdp$_{t-1}$	4.15915	0.00901688
	(1.53019)	(0.0987245)
LIBOR_1m$_{t-1}$	−0.215114	−0.00858658
	(0.0604348)	(0.00389911)
ytm_20yrGilt$_{t-1}$	−0.474067	−0.000381906
	(0.178411)	(0.0115107)
lr_LTDebt_CG$_{t-1}$	−3.29106	−0.237413
	(0.414338)	(0.0267321)

Adjustment vectors

lr_M4_sec$_{t-1}$	1.00000	79.3367
l_gdpdef$_{t-1}$	−0.0149964	1.00000
l_rgdp$_{t-1}$	0.0197157	1.01694
LIBOR_1m$_{t-1}$	−3.53181	−38.4565
ytm_20yrGilt$_{t-1}$	−2.73590	−75.0592
lr_LTDebt_CG$_{t-1}$	−0.264637	−4.37306

Log-likelihood = 788.866

Determinant of covariance matrix = 0.00000

AIC = −22.2146

BIC = −19.5834

HQC = −21.1780

Equation 1: Δlr_M4_sec

	Coefficient	Std. Error	t-ratio	p-value
const	−4.02356	0.798313	−5.040	0.0000
d_lr_M4_sec_1	−0.163601	0.122101	−1.340	0.1859
d_l_gdpdef_1	−0.148232	1.96226	−0.07554	0.9401
d_l_rgdp_1	−5.38373	1.79792	−2.994	0.0041
ΔLIBOR$_{t-1}$	0.0736745	0.0252471	2.918	0.0051
Δytm$_{t-20}$	−0.0759320	0.0442475	−1.716	0.0919
d_lr_LTDebt_CG_1	−0.672807	0.346572	−1.941	0.0574
EC1	−0.118621	0.0371643	−3.192	0.0024
EC2	3.07846	0.591702	5.203	0.0000

Mean dependent var	0.029617	S.D. dependent var	0.088053
Sum squared resid	0.237204	S.E. of regression	0.066277
R^2	0.514382	Adjusted R^2	0.433446
$\hat{\rho}$	0.002255	Durbin–Watson	1.972555

Equation 2: Δl_gdpdef

	Coefficient	Std. Error	t-ratio	p-value
const	−0.140327	0.0555245	−2.527	0.0145
d_lr_M4_sec_1	−0.00590415	0.00849239	−0.6952	0.4899
d_l_gdpdef_1	−0.343118	0.136480	−2.514	0.0149
d_l_rgdp_1	−0.106567	0.125050	−0.8522	0.3979
ΔLIBOR$_{t-1}$	0.00377836	0.00175600	2.152	0.0359
Δytm$_{t-20}$	−0.00498862	0.00307751	−1.621	0.1108
d_lr_LTDebt_CG_1	−0.0545551	0.0241049	−2.263	0.0277
EC1	0.00177889	0.00258486	0.6882	0.4943
EC2	0.0388025	0.0411542	0.9429	0.3500

Mean dependent var	0.004801	S.D. dependent var	0.004818
Sum squared resid	0.001147	S.E. of regression	0.004610
R^2	0.215289	Adjusted R^2	0.084504
$\hat{\rho}$	−0.149334	Durbin–Watson	2.243994

Equation 3: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0254920	0.0563056	−0.4527	0.6525
d_lr_M4_sec_1	−0.0170758	0.00861187	−1.983	0.0525
d_l_gdpdef_1	−0.164668	0.138400	−1.190	0.2393
d_l_rgdp_1	0.646115	0.126809	5.095	0.0000
ΔLIBOR$_{t-1}$	−0.00119854	0.00178070	−0.6731	0.5038
Δytm$_{t-20}$	−0.000371439	0.00312081	−0.1190	0.9057
d_lr_LTDebt_CG_1	−0.00491364	0.0244440	−0.2010	0.8414
EC1	−0.00233869	0.00262123	−0.8922	0.3762
EC2	0.0394597	0.0417332	0.9455	0.3486

Mean dependent var	0.004298	S.D. dependent var	0.006389
Sum squared resid	0.001180	S.E. of regression	0.004675
R^2	0.541106	Adjusted R^2	0.464624
$\hat{\rho}$	−0.052732	Durbin–Watson	2.091531

Equation 4: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	−8.68670	3.35912	−2.586	0.0124
d_lr_M4_sec_1	−1.26866	0.513772	−2.469	0.0167
d_l_gdpdef_1	−9.77459	8.25675	−1.184	0.2417
d_l_rgdp_1	24.7160	7.56524	3.267	0.0019
ΔLIBOR$_{t-1}$	0.431001	0.106234	4.057	0.0002
Δytm$_{t-20}$	0.0425753	0.186183	0.2287	0.8200
d_lr_LTDebt_CG_1	−5.00091	1.45829	−3.429	0.0012
EC1	0.418947	0.156379	2.679	0.0098
EC2	−1.49221	2.48974	−0.5993	0.5515

Mean dependent var	−0.086511	S.D. dependent var	0.429329
Sum squared resid	4.199778	S.E. of regression	0.278879
R^2	0.638336	Adjusted R^2	0.578059
$\hat{\rho}$	−0.015379	Durbin–Watson	1.994864

Equation 5: Δytm_20yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	−2.34572	2.28971	−1.024	0.3102
d_lr_M4_sec_1	0.358443	0.350208	1.024	0.3106
d_l_gdpdef_1	−3.13168	5.62813	−0.5564	0.5802
d_l_rgdp_1	1.17809	5.15678	0.2285	0.8202
ΔLIBOR$_{t-1}$	−0.00984652	0.0724135	−0.1360	0.8923
Δytm$_{t-20}$	−0.179948	0.126910	−1.418	0.1620
d_lr_LTDebt_CG_1	−5.41909	0.994033	−5.452	0.0000
EC1	0.324536	0.106594	3.045	0.0036
EC2	−2.91249	1.69711	−1.716	0.0919

Mean dependent var	−0.039531	S.D. dependent var	0.231049
Sum squared resid	1.951359	S.E. of regression	0.190095
R^2	0.419786	Adjusted R^2	0.323084
$\hat{\rho}$	−0.018085	Durbin–Watson	1.982282

Equation 6: Δlr_LTDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	−0.492279	0.362324	−1.359	0.1799
d_lr_M4_sec_1	−0.0281895	0.0554169	−0.5087	0.6130
d_l_gdpdef_1	1.04369	0.890597	1.172	0.2464
d_l_rgdp_1	−0.988136	0.816009	−1.211	0.2312
ΔLIBOR$_{t-1}$	0.00749605	0.0114587	0.6542	0.5158
Δytm$_{t-20}$	0.0312646	0.0200823	1.557	0.1254
d_lr_LTDebt_CG_1	0.285919	0.157296	1.818	0.0747
EC1	0.0313915	0.0168675	1.861	0.0682
EC2	−0.169686	0.268551	−0.6319	0.5301

Mean dependent var	0.022390	S.D. dependent var	0.034964
Sum squared resid	0.048862	S.E. of regression	0.030081
R^2	0.365549	Adjusted R^2	0.259807
$\hat{\rho}$	0.011345	Durbin–Watson	1.904819

Table A.15: Information criteria for lag selection, system B4e

lags	loglik	p(LR)	AIC	BIC	HQC
1	895.67220		-27.086200	-25.164917*	-26.331856
2	977.57011	0.00000	-28.147423*	-24.545018	-26.733028*
3	1017.51171	0.00349	-27.855216	-22.571689	-25.780770
4	1075.34002	0.00000	-28.140001	-21.175351	-25.405504

B4e, VECM system on log real M4 securitisation, log real GDP, log GDP deflator, 1 month LIBOR, 20-year gilt yield, log real long-term debt outstanding as a liability of central government, and log real deposits in Monetary Financial Institutions held as assets of UK Private Non-Financial Corporates (lr_PNFC_MFI_deposits)

VAR lag selection for system B4e

Table A.16: Trace and maximum eigenvalue tests for system B4e

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.59748	165.44 [0.0000]	58.241 [0.0008]
1	0.46435	107.20 [0.0056]	39.954 [0.0477]
2	0.41641	67.243 [0.0771]	34.467 [0.0385]
3	0.22550	32.776 [0.5734]	16.355 [0.6425]
4	0.14422	16.421 [0.6892]	9.9677 [0.7502]
5	0.094812	6.4534 [0.6467]	6.3752 [0.5728]
6	0.0012200	0.078127 [0.7799]	0.078127 [0.7799]

Johansen rank selection for system B4e

Model B4e

VECM system, lag order 2

Maximum likelihood estimates, observations 2000:3–2016:2 ($T = 64$)

Cointegration rank = 2

Case 3: Unrestricted constant

Cointegrating vectors (standard errors in parentheses)

lr_M4_sec$_{t-1}$	1.00000	0.00000
	(0.00000)	(0.00000)
l_gdpdef$_{t-1}$	0.00000	1.00000
	(0.00000)	(0.00000)
l_rgdp$_{t-1}$	1.64947	−0.256491
	(4.36084)	(0.252107)
LIBOR_1m$_{t-1}$	−0.232189	−0.00969886
	(0.0609398)	(0.00352302)
ytm_20yrGilt$_{t-1}$	−0.383155	0.00389188
	(0.213965)	(0.0123696)
lr_LTDebt_CG$_{t-1}$	−3.37919	−0.240485
	(0.571246)	(0.0330246)
lr_PNFC_MFI_deposits$_{t-1}$	1.40989	0.123122
	(2.16446)	(0.125131)

Adjustment vectors

lr_M4_sec$_{t-1}$	1.00000	109.992
l_gdpdef$_{t-1}$	−0.0149850	1.00000
l_rgdp$_{t-1}$	0.0203989	1.71087
LIBOR_1m$_{t-1}$	−3.12487	−53.5566
ytm_20yrGilt$_{t-1}$	−2.57672	−113.490
lr_LTDebt_CG$_{t-1}$	−0.202185	−3.53857
lr_PNFC_MFI_deposits$_{t-1}$	−0.0265532	−9.06060

Log-likelihood = 966.628

Determinant of covariance matrix = 0.00000

AIC = −26.9259

BIC = −23.3839

HQC = −25.5305

Equation 1: Δlr_M4_sec

	Coefficient	Std. Error	t-ratio	p-value
const	1.11195	0.315651	3.523	0.0009
d_lr_M4_sec_1	−0.111933	0.120504	−0.9289	0.3572
d_l_gdpdef_1	0.477883	2.00350	0.2385	0.8124
d_l_rgdp_1	−5.49677	1.82393	−3.014	0.0040
ΔLIBOR$_{t-1}$	0.0811123	0.0255594	3.173	0.0025
Δytm$_{t-20}$	−0.0951529	0.0457080	−2.082	0.0422
d_lr_LTDebt_CG_1	−0.691931	0.352069	−1.965	0.0546
d_lr_PNFC_MFI_deposits_1	0.493697	0.394537	1.251	0.2163
EC1	−0.133980	0.0401527	−3.337	0.0016
EC2	3.41059	0.684681	4.981	0.0000

Mean dependent var	0.029617	S.D. dependent var	0.088053
Sum squared resid	0.235793	S.E. of regression	0.066700
R^2	0.517271	Adjusted R^2	0.426190
$\hat{\rho}$	0.037135	Durbin–Watson	1.917205

Equation 2: Δl_gdpdef

	Coefficient	Std. Error	t-ratio	p-value
const	−0.00820795	0.0219236	−0.3744	0.7096
d_lr_M4_sec_1	−0.00314527	0.00836961	−0.3758	0.7086
d_l_gdpdef_1	−0.297178	0.139153	−2.136	0.0373
d_l_rgdp_1	−0.120241	0.126681	−0.9492	0.3468
ΔLIBOR$_{t-1}$	0.00407666	0.00177523	2.296	0.0256
Δytm$_{t-20}$	−0.00550482	0.00317465	−1.734	0.0887
d_lr_LTDebt_CG_1	−0.0552086	0.0244529	−2.258	0.0281
d_lr_PNFC_MFI_deposits_1	0.0324503	0.0274026	1.184	0.2416
EC1	0.00200768	0.00278881	0.7199	0.4747
EC2	0.0310076	0.0475545	0.6520	0.5172

Mean dependent var	0.004801	S.D. dependent var	0.004818
Sum squared resid	0.001137	S.E. of regression	0.004633
R^2	0.222138	Adjusted R^2	0.075371
$\hat{\rho}$	−0.117855	Durbin–Watson	2.193254

Equation 3: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.0238348	0.0219543	1.086	0.2825
d_lr_M4_sec_1	−0.0170698	0.00838133	−2.037	0.0467
d_l_gdpdef_1	−0.144089	0.139348	−1.034	0.3058
d_l_rgdp_1	0.625412	0.126859	4.930	0.0000
ΔLIBOR_{t-1}	−0.000942162	0.00177772	−0.5300	0.5983
Δytm_{t-20}	−0.000957516	0.00317909	−0.3012	0.7644
d_lr_LTDebt_CG_1	−0.00540357	0.0244872	−0.2207	0.8262
d_lr_PNFC_MFI_deposits_1	0.0311130	0.0274409	1.134	0.2620
EC1	−0.00273304	0.00279271	−0.9786	0.3322
EC2	0.0530500	0.0476211	1.114	0.2703

Mean dependent var	0.004298	S.D. dependent var	0.006389
Sum squared resid	0.001141	S.E. of regression	0.004639
R^2	0.556406	Adjusted R^2	0.472709
$\hat{\rho}$	−0.080243	Durbin–Watson	2.133639

Equation 4: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	−3.29042	1.31351	−2.505	0.0154
d_lr_M4_sec_1	−1.19838	0.501449	−2.390	0.0204
d_l_gdpdef_1	−7.62399	8.33708	−0.9145	0.3646
d_l_rgdp_1	23.6902	7.58986	3.121	0.0029
ΔLIBOR$_{t-1}$	0.447422	0.106359	4.207	0.0001
Δytm$_{t-20}$	−0.00504913	0.190203	−0.02655	0.9789
d_lr_LTDebt_CG_1	−5.13138	1.46505	−3.503	0.0009
d_lr_PNFC_MFI_deposits_1	1.83447	1.64177	1.117	0.2689
EC1	0.418669	0.167086	2.506	0.0153
EC2	−1.66066	2.84914	−0.5829	0.5625

Mean dependent var	−0.086511	S.D. dependent var	0.429329
Sum squared resid	4.083014	S.E. of regression	0.277557
R^2	0.648391	Adjusted R^2	0.582050
$\hat{\rho}$	−0.049210	Durbin–Watson	2.072402

Equation 5: Δytm_20yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	−2.67147	0.893982	−2.988	0.0042
d_lr_M4_sec_1	0.412972	0.341290	1.210	0.2316
d_l_gdpdef_1	−1.19596	5.67427	−0.2108	0.8339
d_l_rgdp_1	0.0983520	5.16571	0.01904	0.9849
ΔLIBOR$_{t-1}$	−0.00166212	0.0723890	−0.02296	0.9818
Δytm$_{t-20}$	−0.192523	0.129453	−1.487	0.1429
d_lr_LTDebt_CG_1	−5.41928	0.997122	−5.435	0.0000
d_lr_PNFC_MFI_deposits_1	1.64091	1.11740	1.469	0.1479
EC1	0.345228	0.113720	3.036	0.0037
EC2	−3.51905	1.93914	−1.815	0.0752

Mean dependent var	−0.039531	S.D. dependent var	0.231049
Sum squared resid	1.891357	S.E. of regression	0.188907
R^2	0.437627	Adjusted R^2	0.331519
$\hat{\rho}$	−0.061198	Durbin–Watson	2.093640

Equation 6: Δlr_LTDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	−0.191627	0.140691	−1.362	0.1789
d_lr_M4_sec_1	−0.0374205	0.0537107	−0.6967	0.4890
d_l_gdpdef_1	0.809786	0.892993	0.9068	0.3686
d_l_rgdp_1	−0.836766	0.812957	−1.029	0.3080
ΔLIBOR$_{t-1}$	0.00641706	0.0113923	0.5633	0.5756
Δytm$_{t-20}$	0.0291567	0.0203728	1.431	0.1583
d_lr_LTDebt_CG_1	0.269950	0.156923	1.720	0.0912
d_lr_PNFC_MFI_deposits_1	−0.236840	0.175852	−1.347	0.1838
EC1	0.0270887	0.0178967	1.514	0.1361
EC2	−0.109722	0.305174	−0.3595	0.7206

Mean dependent var	0.022390	S.D. dependent var	0.034964
Sum squared resid	0.046843	S.E. of regression	0.029729
R^2	0.391758	Adjusted R^2	0.276995
$\hat{\rho}$	−0.002914	Durbin–Watson	1.929953

Equation 7: Δlr_PNFC_MFI_d

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0255874	0.0903292	−0.2833	0.7781
d_lr_M4_sec_1	0.111241	0.0344844	3.226	0.0022
d_l_gdpdef_1	−0.511422	0.573336	−0.8920	0.3764
d_l_rgdp_1	1.66067	0.521950	3.182	0.0024
ΔLIBOR$_{t-1}$	−0.00465654	0.00731428	−0.6366	0.5271
Δytm$_{t-20}$	0.0141228	0.0130801	1.080	0.2852
d_lr_LTDebt_CG_1	0.219361	0.100751	2.177	0.0339
d_lr_PNFC_MFI_deposits_1	−0.269996	0.112904	−2.391	0.0204
EC1	0.00355760	0.0114904	0.3096	0.7581
EC2	−0.280947	0.195934	−1.434	0.1575

Mean dependent var	0.010924	S.D. dependent var	0.021537
Sum squared resid	0.019310	S.E. of regression	0.019087
R^2	0.339189	Adjusted R^2	0.214508
$\hat{\rho}$	0.192806	Durbin–Watson	1.597545

B4f, VECM system on log real M4 securitisation, log real GDP, log GDP deflator, 1 month LIBOR, 20-year gilt yield, log real long-term debt outstanding as a liability of central government, log real deposits in Monetary Financial Institutions held as assets of UK Private Non-Financial Corporates, and contemporaneous FTSE 100 realised volatility (in short-run equations only)

VECM system, lag order 2

Maximum likelihood estimates, observations 2000:3–2016:2 ($T = 64$)

Cointegration rank = 2

Case 3: Unrestricted constant

Restrictions on beta: b[1,1] = -1 b[1,2] = 0 b[2,1] = 0 b[2,2] = -1

Cointegrating vectors (standard errors in parentheses)

lr_M4_sec_{t-1}	-1.00000	0.00000
	(0.00000)	(0.00000)
l_gdpdef_{t-1}	0.00000	-1.00000
	(0.00000)	(0.00000)
l_rgdp_{t-1}	-11.9356	0.678709
	(7.02852)	(0.158050)
LIBOR_1m_{t-1}	0.298670	0.00777223
	(0.0978904)	(0.00220125)
$\text{ytm\_20yrGilt}_{t-1}$	-0.277951	0.0201613
	(0.345082)	(0.00775982)
$\text{lr\_LTDebt\_CG}_{t-1}$	3.89871	0.225157
	(0.918025)	(0.0206435)
$\text{lr\_PNFC\_MFI\_deposits}_{t-1}$	-0.357625	-0.180049
	(3.47773)	(0.0782033)

Adjustment vectors (standard errors in parentheses)

$lr\_M4\_sec_{t-1}$	-0.0571836	0.616420
	(0.0273628)	(1.20677)
l_gdpdef_{t-1}	-0.00389074	0.0703436
	(0.00169991)	(0.0749706)
l_rgdp_{t-1}	0.00550362	-0.264296
	(0.00149527)	(0.0659453)
$LIBOR\_1m_{t-1}$	-0.0727362	-5.26022
	(0.0952487)	(4.20071)
$ytm\_20yrGilt_{t-1}$	0.133360	-9.63428
	(0.0649533)	(2.86461)
$lr\_LTDebt\_CG_{t-1}$	-0.0141666	0.0866862
	(0.0110553)	(0.487568)
$lr\_PNFC\_MFI\_deposits_{t-1}$	0.0221308	-0.632921
	(0.00667464)	(0.294369)

Log-likelihood = 985.954

Determinant of covariance matrix = 0.00000

AIC = -27.3111

BIC = -23.5330

HQC = -25.8227

Equation 1: Δlr_M4_sec

	Coefficient	Std. Error	t-ratio	p-value
const	-10.5090	9.27601	-1.133	0.2624
d_lr_M4_sec_1	-0.0546572	0.134898	-0.4052	0.6870
d_l_gdpdef_1	2.38062	2.23330	1.066	0.2914
d_l_rgdp_1	-3.49364	2.14010	-1.632	0.1086
$\Delta LIBOR_{t-1}$	0.0822294	0.0310819	2.646	0.0108
Δytm_{t-20}	-0.0550258	0.0494216	-1.113	0.2707
d_lr_LTDebt_CG_1	-1.15013	0.389362	-2.954	0.0047
d_lr_PNFC_MFI_deposits_1	0.868084	0.442456	1.962	0.0551
FTSE_Vol	0.00247224	0.00111104	2.225	0.0304
EC1	-0.0571836	0.0273628	-2.090	0.0415
EC2	0.616420	1.20677	0.5108	0.6117

Mean dependent var	0.029617	S.D. dependent var	0.088053
Sum squared resid	0.278614	S.E. of regression	0.073198
R^2	0.429606	Adjusted R^2	0.308945
$\hat{\rho}$	−0.078949	Durbin–Watson	2.147703

Equation 2: Δl_gdpdef

	Coefficient	Std. Error	t-ratio	p-value
const	−0.849929	0.576273	−1.475	0.1463
d_lr_M4_sec_1	−0.00944595	0.00838057	−1.127	0.2649
d_l_gdpdef_1	−0.249640	0.138744	−1.799	0.0778
d_l_rgdp_1	−0.103109	0.132954	−0.7755	0.4415
ΔLIBOR_{t-1}	0.00278184	0.00193096	1.441	0.1557
Δytm_{t-20}	−0.00553021	0.00307032	−1.801	0.0775
d_lr_LTDebt_CG_1	−0.0638612	0.0241892	−2.640	0.0109
d_lr_PNFC_MFI_deposits_1	0.0427010	0.0274876	1.553	0.1264
FTSE_Vol	6.78124e–005	6.90235e–005	0.9825	0.3304
EC1	−0.00389074	0.00169991	−2.289	0.0262
EC2	0.0703436	0.0749706	0.9383	0.3524

Mean dependent var	0.004801	S.D. dependent var	0.004818
Sum squared resid	0.001075	S.E. of regression	0.004547
R^2	0.264636	Adjusted R^2	0.109078
$\hat{\rho}$	−0.143692	Durbin–Watson	2.234701

Equation 3: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	2.03404	0.506898	4.013	0.0002
d_lr_M4_sec_1	−0.000802620	0.00737167	−0.1089	0.9137
d_l_gdpdef_1	−0.244114	0.122041	−2.000	0.0507
d_l_rgdp_1	0.595225	0.116948	5.090	0.0000
ΔLIBOR$_{t-1}$	0.00240610	0.00169850	1.417	0.1626
Δytm$_{t-20}$	−0.000673632	0.00270070	−0.2494	0.8040
d_lr_LTDebt_CG_1	0.0109813	0.0212772	0.5161	0.6080
d_lr_PNFC_MFI_deposits_1	0.00882989	0.0241785	0.3652	0.7164
FTSE_Vol	−0.000148782	6.07141e–005	−2.451	0.0177
EC1	0.00550362	0.00149527	3.681	0.0006
EC2	−0.264296	0.0659453	−4.008	0.0002

Mean dependent var	0.004298	S.D. dependent var	0.006389
Sum squared resid	0.000832	S.E. of regression	0.004000
R^2	0.676440	Adjusted R^2	0.607995
$\hat{\rho}$	−0.141604	Durbin–Watson	2.264331

Equation 4: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	16.9623	32.2894	0.5253	0.6016
d_lr_M4_sec_1	−1.02363	0.469576	−2.180	0.0338
d_l_gdpdef_1	−11.9085	7.77401	−1.532	0.1316
d_l_rgdp_1	12.7334	7.44962	1.709	0.0934
ΔLIBOR$_{t-1}$	0.443894	0.108195	4.103	0.0001
Δytm$_{t-20}$	−0.109193	0.172035	−0.6347	0.5284
d_lr_LTDebt_CG_1	−4.24914	1.35536	−3.135	0.0028
d_lr_PNFC_MFI_deposits_1	0.682216	1.54017	0.4429	0.6596
FTSE_Vol	−0.0148968	0.00386749	−3.852	0.0003
EC1	−0.0727362	0.0952487	−0.7636	0.4485
EC2	−5.26022	4.20071	−1.252	0.2161

Mean dependent var	−0.086511	S.D. dependent var	0.429329
Sum squared resid	3.375995	S.E. of regression	0.254800
R^2	0.709276	Adjusted R^2	0.647777
$\hat{\rho}$	−0.101352	Durbin–Watson	2.176305

Equation 5: Δytm_20yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	65.4218	22.0192	2.971	0.0045
d_lr_M4_sec_1	0.640652	0.320219	2.001	0.0507
d_l_gdpdef_1	−7.40365	5.30136	−1.397	0.1685
d_l_rgdp_1	−5.33714	5.08014	−1.051	0.2983
ΔLIBOR$_{t-1}$	0.0673599	0.0737816	0.9130	0.3655
Δytm$_{t-20}$	−0.278010	0.117316	−2.370	0.0215
d_lr_LTDebt_CG_1	−4.05817	0.924263	−4.391	0.0001
d_lr_PNFC_MFI_deposits_1	0.325578	1.05030	0.3100	0.7578
FTSE_Vol	−0.00892829	0.00263737	−3.385	0.0014
EC1	0.133360	0.0649533	2.053	0.0451
EC2	−9.63428	2.86461	−3.363	0.0015

Mean dependent var	−0.039531	S.D. dependent var	0.231049
Sum squared resid	1.569950	S.E. of regression	0.173757
R^2	0.533194	Adjusted R^2	0.434446
$\hat{\rho}$	0.046460	Durbin–Watson	1.872677

Equation 6: Δlr_LTDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	−2.27136	3.74777	−0.6061	0.5471
d_lr_M4_sec_1	−0.0879912	0.0545027	−1.614	0.1125
d_l_gdpdef_1	0.876730	0.902314	0.9716	0.3357
d_l_rgdp_1	−0.499507	0.864662	−0.5777	0.5660
ΔLIBOR$_{t-1}$	0.00127688	0.0125579	0.1017	0.9194
Δytm$_{t-20}$	0.0266269	0.0199677	1.333	0.1882
d_lr_LTDebt_CG_1	0.282170	0.157313	1.794	0.0787
d_lr_PNFC_MFI_deposits_1	−0.203796	0.178765	−1.140	0.2595
FTSE_Vol	0.000729558	0.000448891	1.625	0.1102
EC1	−0.0141666	0.0110553	−1.281	0.2057
EC2	0.0866862	0.487568	0.1778	0.8596

Mean dependent var	0.022390	S.D. dependent var	0.034964
Sum squared resid	0.045481	S.E. of regression	0.029574
R^2	0.409453	Adjusted R^2	0.284530
$\hat{\rho}$	0.051578	Durbin–Watson	1.818612

Equation 7: Δlr_PNFC_MFI_d

	Coefficient	Std. Error	t-ratio	p-value
const	6.03582	2.26271	2.668	0.0102
d_lr_M4_sec_1	0.141265	0.0329059	4.293	0.0001
d_l_gdpdef_1	−0.919859	0.544771	−1.689	0.0973
d_l_rgdp_1	1.51641	0.522038	2.905	0.0054
ΔLIBOR$_{t-1}$	0.00332076	0.00758184	0.4380	0.6632
Δytm$_{t-20}$	0.0116627	0.0120555	0.9674	0.3378
d_lr_LTDebt_CG_1	0.306217	0.0949778	3.224	0.0022
d_lr_PNFC_MFI_deposits_1	−0.353337	0.107929	−3.274	0.0019
FTSE_Vol	−0.000426558	0.000271018	−1.574	0.1216
EC1	0.0221308	0.00667464	3.316	0.0017
EC2	−0.632921	0.294369	−2.150	0.0362

Mean dependent var	0.010924	S.D. dependent var	0.021537
Sum squared resid	0.016578	S.E. of regression	0.017855
R^2	0.432658	Adjusted R^2	0.312644
$\hat{\rho}$	0.035792	Durbin–Watson	1.907162

B4g, VECM system of same composition as B4f but with lagged FTSE volatility in short-run equations

VECM system, lag order 2

Maximum likelihood estimates, observations 2000:3–2016:2 ($T = 64$)

Cointegration rank = 2

Case 3: Unrestricted constant

Restrictions on beta: b[1,1] = -1 b[1,2] = 0 b[2,1] = 0 b[2,2] = -1

Cointegrating vectors (standard errors in parentheses)

lr_M4_sec$_{t-1}$	-1.00000	0.00000
	(0.00000)	(0.00000)
l_gdpdef$_{t-1}$	0.00000	-1.00000
	(0.00000)	(0.00000)
l_rgdp$_{t-1}$	39.2880	0.390668
	(14.4618)	(0.262048)
LIBOR_1m$_{t-1}$	0.0233637	0.0110085
	(0.192625)	(0.00349038)
ytm_20yrGilt$_{t-1}$	3.21607	0.00140918
	(0.690938)	(0.0125198)
lr_LTDebt_CG$_{t-1}$	1.85093	0.255430
	(1.83133)	(0.0331838)
lr_PNFC_MFI_deposits$_{t-1}$	-5.90349	-0.176024
	(7.00448)	(0.126922)

Adjustment vectors (standard errors in parentheses)

$lr\_M4\_sec_{t-1}$	0.0307592	−0.466006
	(0.00993404)	(0.453193)
l_gdpdef_{t-1}	0.000334583	−0.0516170
	(0.000684615)	(0.0312323)
l_rgdp_{t-1}	−0.00107524	−0.0510168
	(0.000670832)	(0.0306035)
$LIBOR\_1m_{t-1}$	−0.0834168	−6.95224
	(0.0373538)	(1.70409)
$ytm\_20yrGilt_{t-1}$	−0.100418	−4.84181
	(0.0265642)	(1.21187)
$lr\_LTDebt\_CG_{t-1}$	−0.00311761	−0.362989
	(0.00433776)	(0.197890)
$lr\_PNFC\_MFI\_deposits_{t-1}$	−0.00607654	0.0442925
	(0.00267557)	(0.122060)

Log-likelihood = 976.936

Determinant of covariance matrix = 0.00000

AIC = −27.0292

BIC = −23.2512

HQC = −25.5409

Equation 1: Δlr_M4_sec

	Coefficient	Std. Error	t-ratio	p-value
const	−14.1336	5.26480	−2.685	0.0097
d_lr_M4_sec_1	−0.175205	0.131261	−1.335	0.1878
d_l_gdpdef_1	0.976367	2.09075	0.4670	0.6425
d_l_rgdp_1	−5.35791	1.88515	−2.842	0.0064
$\Delta LIBOR_{t-1}$	0.0864890	0.0313690	2.757	0.0080
Δytm_{t-20}	−0.0803863	0.0471503	−1.705	0.0942
d_lr_LTDebt_CG_1	−1.14018	0.349426	−3.263	0.0020
d_lr_PNFC_MFI_deposits_1	0.697880	0.400810	1.741	0.0876
FTSE_Vol_1	0.00175840	0.00125787	1.398	0.1681
EC1	0.0307592	0.00993404	3.096	0.0032
EC2	−0.466006	0.453193	−1.028	0.3086

Mean dependent var	0.029617	S.D. dependent var	0.088053
Sum squared resid	0.240664	S.E. of regression	0.068031
R^2	0.507299	Adjusted R^2	0.403073
$\hat{\rho}$	0.017993	Durbin–Watson	1.959172

Equation 2: Δl_gdpdef

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0780815	0.362829	−0.2152	0.8305
d_lr_M4_sec_1	−0.00609627	0.00904597	−0.6739	0.5033
d_l_gdpdef_1	−0.302825	0.144086	−2.102	0.0404
d_l_rgdp_1	−0.138495	0.129917	−1.066	0.2913
ΔLIBOR_{t-1}	0.00374952	0.00216183	1.734	0.0888
Δytm_{t-20}	−0.00591313	0.00324941	−1.820	0.0746
d_lr_LTDebt_CG_1	−0.0493926	0.0240811	−2.051	0.0453
d_lr_PNFC_MFI_deposits_1	0.0297935	0.0276222	1.079	0.2857
FTSE_Vol_1	8.61554e–006	8.66873e–005	0.09939	0.9212
EC1	0.000334583	0.000684615	0.4887	0.6271
EC2	−0.0516170	0.0312323	−1.653	0.1044

Mean dependent var	0.004801	S.D. dependent var	0.004818
Sum squared resid	0.001143	S.E. of regression	0.004688
R^2	0.218341	Adjusted R^2	0.052990
$\hat{\rho}$	−0.126116	Durbin–Watson	2.212847

Equation 3: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.596566	0.355525	1.678	0.0994
d_lr_M4_sec_1	−0.0104696	0.00886384	−1.181	0.2429
d_l_gdpdef_1	−0.163130	0.141185	−1.155	0.2532
d_l_rgdp_1	0.662642	0.127302	5.205	0.0000
ΔLIBOR$_{t-1}$	0.000994934	0.00211830	0.4697	0.6405
Δytm$_{t-20}$	−5.81941e–005	0.00318399	−0.01828	0.9855
d_lr_LTDebt_CG_1	−0.0153699	0.0235962	−0.6514	0.5177
d_lr_PNFC_MFI_deposits_1	0.0307461	0.0270661	1.136	0.2612
FTSE_Vol_1	1.75551e–005	8.49421e–005	0.2067	0.8371
EC1	−0.00107524	0.000670832	−1.603	0.1150
EC2	−0.0510168	0.0306035	−1.667	0.1015

Mean dependent var	0.004298	S.D. dependent var	0.006389
Sum squared resid	0.001097	S.E. of regression	0.004594
R^2	0.573205	Adjusted R^2	0.482921
$\hat{\rho}$	−0.114752	Durbin–Watson	2.214886

Equation 4: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	50.8007	19.7966	2.566	0.0132
d_lr_M4_sec_1	−0.684951	0.493564	−1.388	0.1711
d_l_gdpdef_1	−4.11303	7.86161	−0.5232	0.6031
d_l_rgdp_1	19.6295	7.08851	2.769	0.0078
ΔLIBOR$_{t-1}$	0.305250	0.117953	2.588	0.0125
Δytm$_{t-20}$	−0.125953	0.177294	−0.7104	0.4806
d_lr_LTDebt_CG_1	−2.73661	1.31391	−2.083	0.0422
d_lr_PNFC_MFI_deposits_1	1.01165	1.50712	0.6712	0.5050
FTSE_Vol_1	−0.0175007	0.00472982	−3.700	0.0005
EC1	−0.0834168	0.0373538	−2.233	0.0299
EC2	−6.95224	1.70409	−4.080	0.0002

Mean dependent var	−0.086511	S.D. dependent var	0.429329
Sum squared resid	3.402752	S.E. of regression	0.255808
R^2	0.706972	Adjusted R^2	0.644985
$\hat{\rho}$	0.016859	Durbin–Watson	1.921060

Equation 5: Δytm_20yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	55.6953	14.0784	3.956	0.0002
d_lr_M4_sec_1	0.672389	0.350999	1.916	0.0609
d_l_gdpdef_1	−3.66033	5.59079	−0.6547	0.5155
d_l_rgdp_1	0.362009	5.04101	0.07181	0.9430
ΔLIBOR$_{t-1}$	0.0562197	0.0838826	0.6702	0.5057
Δytm$_{t-20}$	−0.201613	0.126083	−1.599	0.1159
d_lr_LTDebt_CG_1	−4.33125	0.934386	−4.635	0.0000
d_lr_PNFC_MFI_deposits_1	0.930537	1.07179	0.8682	0.3893
FTSE_Vol_1	−0.00207843	0.00336362	−0.6179	0.5393
EC1	−0.100418	0.0265642	−3.780	0.0004
EC2	−4.84181	1.21187	−3.995	0.0002

Mean dependent var	−0.039531	S.D. dependent var	0.231049
Sum squared resid	1.720896	S.E. of regression	0.181918
R^2	0.488312	Adjusted R^2	0.380070
$\hat{\rho}$	−0.029872	Durbin–Watson	2.019962

Equation 6: Δlr_LTDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	2.07728	2.29891	0.9036	0.3704
d_lr_M4_sec_1	−0.0160791	0.0573158	−0.2805	0.7802
d_l_gdpdef_1	1.05164	0.912939	1.152	0.2546
d_l_rgdp_1	−1.12112	0.823163	−1.362	0.1791
ΔLIBOR$_{t-1}$	−0.00435808	0.0136975	−0.3182	0.7516
Δytm$_{t-20}$	0.0214891	0.0205885	1.044	0.3014
d_lr_LTDebt_CG_1	0.422391	0.152579	2.768	0.0078
d_lr_PNFC_MFI_deposits_1	−0.283451	0.175016	−1.620	0.1114
FTSE_Vol_1	−0.00101259	0.000549256	−1.844	0.0709
EC1	−0.00311761	0.00433776	−0.7187	0.4755
EC2	−0.362989	0.197890	−1.834	0.0723

Mean dependent var	0.022390	S.D. dependent var	0.034964
Sum squared resid	0.045887	S.E. of regression	0.029706
R^2	0.404174	Adjusted R^2	0.278134
$\hat{\rho}$	0.000851	Durbin–Watson	1.918937

Equation 7: Δlr_PNFC_MFI_d

	Coefficient	Std. Error	t-ratio	p-value
const	2.87737	1.41799	2.029	0.0476
d_lr_M4_sec_1	0.144408	0.0353528	4.085	0.0002
d_l_gdpdef_1	−0.491298	0.563109	−0.8725	0.3870
d_l_rgdp_1	1.71411	0.507734	3.376	0.0014
ΔLIBOR$_{t-1}$	−0.00314489	0.00844872	−0.3722	0.7112
Δytm$_{t-20}$	0.0144284	0.0126991	1.136	0.2611
d_lr_LTDebt_CG_1	0.250243	0.0941120	2.659	0.0104
d_lr_PNFC_MFI_deposits_1	−0.286470	0.107951	−2.654	0.0105
FTSE_Vol_1	−0.000381350	0.000338786	−1.126	0.2655
EC1	−0.00607654	0.00267557	−2.271	0.0273
EC2	0.0442925	0.122060	0.3629	0.7182

Table A.17: Information criteria for lag selection, system B4h

lags	loglik	p(LR)	AIC	BIC	HQC
1	748.37955		-18.712961	-16.969344*	-18.017411
2	837.28846	0.00000	-19.791580*	-16.522299	-18.487423*
3	885.44908	0.00006	-19.768894	-14.973948	-17.856131
4	934.53258	0.00004	-19.771151	-13.450540	-17.249781

Mean dependent var	0.010924	S.D. dependent var	0.021537
Sum squared resid	0.017458	S.E. of regression	0.018323
R^2	0.402556	Adjusted R^2	0.276173
$\hat{\rho}$	0.118762	Durbin–Watson	1.727330

B4h, VECM system on log real non-core funding measure (lr_noncore), log real GDP, RPI, 1 month LIBOR, 10-year gilt yield, log real long-term debt outstanding as a liability of central government, and log real deposits in Monetary Financial Institutions held as assets of UK Private Non-Financial Corporates (lr_PNFC_MFI_deposits)

VAR lag selection for system B4h

Table A.18: Trace and maximum eigenvalue tests for system B4h

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.59816	183.49 [0.0000]	69.290 [0.0000]
1	0.45069	114.20 [0.0012]	45.532 [0.0080]
2	0.29573	68.670 [0.0596]	26.646 [0.2926]
3	0.26416	42.024 [0.1586]	23.312 [0.1638]
4	0.16177	18.712 [0.5243]	13.411 [0.4296]
5	0.060417	5.3012 [0.7757]	4.7362 [0.7732]
6	0.0074067	0.56500 [0.4523]	0.56500 [0.4523]

Johansen rank selection for system B4h

Model B4h

VECM system, lag order 2

Maximum likelihood estimates, observations 2000:2–2016:2 ($T = 65$)

Cointegration rank = 2

Case 3: Unrestricted constant

Cointegrating vectors (standard errors in parentheses)

lr_noncore$_{t-1}$	1.00000	0.00000
	(0.00000)	(0.00000)
RPI$_{t-1}$	0.00000	1.00000
	(0.00000)	(0.00000)
l_rgdp$_{t-1}$	69.4887	504.168
	(121.946)	(916.268)
LIBOR_1m$_{t-1}$	8.24134	62.0216
	(2.10519)	(15.8178)
ytm_10yrGilt$_{t-1}$	−4.58552	−34.1747
	(4.98048)	(37.4219)
lr_LTDebt_CG$_{t-1}$	−7.91261	−55.9429
	(14.4534)	(108.598)
lr_PNFC_MFI_deposits$_{t-1}$	−1.79009	−3.65625
	(59.6338)	(448.070)

Adjustment vectors

lr_noncore$_{t-1}$	1.00000	0.0241100
RPI$_{t-1}$	40.5493	1.00000
l_rgdp$_{t-1}$	0.00704295	0.000204794
LIBOR_1m$_{t-1}$	6.11046	0.150818
ytm_10yrGilt$_{t-1}$	8.58164	0.211116
lr_LTDebt_CG$_{t-1}$	0.264533	0.00658900
lr_PNFC_MFI_deposits$_{t-1}$	0.114252	0.00291506

Log-likelihood = 727.646

Determinant of covariance matrix = 0.00000

AIC = −18.9430

BIC = −15.1963

HQC = −17.4647

Equation 1: Δlr_noncore

	Coefficient	Std. Error	t-ratio	p-value
const	−3.24949	0.621753	−5.226	0.0000
d_lr_noncore_1	−0.200929	0.141201	−1.423	0.1606
$\Delta \mathrm{RPI}_{t-1}$	0.0145792	0.00556203	2.621	0.0114
d_l_rgdp_1	−1.70509	0.693611	−2.458	0.0173
$\Delta \mathrm{LIBOR}_{t-1}$	0.0158241	0.0144367	1.096	0.2780
$\Delta \mathrm{ytm}_{t-10}$	0.00679798	0.0157886	0.4306	0.6685
d_lr_LTDebt_CG_1	−0.00816026	0.140954	−0.05789	0.9541
d_lr_PNFC_MFI_deposits_1	0.253435	0.143803	1.762	0.0838
FTSE_Vol_1	6.80326e–005	0.000440918	0.1543	0.8780
EC1	0.0775325	0.0214747	3.610	0.0007
EC2	−0.0100962	0.00285163	−3.540	0.0008

Mean dependent var	0.010741	S.D. dependent var	0.033930
Sum squared resid	0.033344	S.E. of regression	0.025083
R^2	0.547437	Adjusted R^2	0.453509
$\hat{\rho}$	−0.114476	Durbin–Watson	2.185167

Equation 2: ΔRPI

	Coefficient	Std. Error	t-ratio	p-value
const	−75.7597	12.0207	−6.302	0.0000
d_lr_noncore_1	−1.24109	2.72991	−0.4546	0.6512
ΔRPI_{t-1}	0.481275	0.107534	4.476	0.0000
d_l_rgdp_1	9.52784	13.4100	0.7105	0.4805
ΔLIBOR_{t-1}	0.894809	0.279114	3.206	0.0023
Δytm_{t-10}	−0.672875	0.305250	−2.204	0.0319
d_lr_LTDebt_CG_1	−10.3373	2.72513	−3.793	0.0004
d_lr_PNFC_MFI_deposits_1	6.91777	2.78022	2.488	0.0160
FTSE_Vol_1	−0.00236292	0.00852452	−0.2772	0.7827
EC1	3.14389	0.415182	7.572	0.0000
EC2	−0.418756	0.0551322	−7.595	0.0000

Mean dependent var	−0.013846	S.D. dependent var	0.809490
Sum squared resid	12.46370	S.E. of regression	0.484937
R^2	0.702803	Adjusted R^2	0.641121
$\hat{\rho}$	−0.131058	Durbin–Watson	2.252940

Equation 3: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.0667205	0.117730	0.5667	0.5733
d_lr_noncore_1	0.0172274	0.0267365	0.6443	0.5221
ΔRPI_{t-1}	−0.000286381	0.00105317	−0.2719	0.7867
d_l_rgdp_1	0.664820	0.131336	5.062	0.0000
ΔLIBOR_{t-1}	0.000290958	0.00273361	0.1064	0.9156
Δytm_{t-10}	−0.00148051	0.00298959	−0.4952	0.6225
d_lr_LTDebt_CG_1	−0.0183381	0.0266897	−0.6871	0.4950
d_lr_PNFC_MFI_deposits_1	0.0440186	0.0272292	1.617	0.1119
FTSE_Vol_1	−7.29696e–006	8.34883e–005	−0.08740	0.9307
EC1	0.000546057	0.00406625	0.1343	0.8937
EC2	−8.57588e–005	0.000539959	−0.1588	0.8744

Mean dependent var	0.004343	S.D. dependent var	0.006349
Sum squared resid	0.001196	S.E. of regression	0.004749
R^2	0.536631	Adjusted R^2	0.440461
$\hat{\rho}$	−0.095632	Durbin–Watson	2.182800

Equation 4: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	−10.8850	6.71295	−1.621	0.1108
d_lr_noncore_1	−1.86870	1.52452	−1.226	0.2257
ΔRPI_{t-1}	0.0807005	0.0600521	1.344	0.1847
d_l_rgdp_1	16.4795	7.48878	2.201	0.0321
ΔLIBOR_{t-1}	0.187351	0.155871	1.202	0.2347
Δytm_{t-10}	−0.0195910	0.170467	−0.1149	0.9089
d_lr_LTDebt_CG_1	−2.08699	1.52185	−1.371	0.1760
d_lr_PNFC_MFI_deposits_1	1.88981	1.55261	1.217	0.2289
FTSE_Vol_1	−0.0166650	0.00476051	−3.501	0.0009
EC1	0.473759	0.231858	2.043	0.0460
EC2	−0.0631559	0.0307885	−2.051	0.0452

Mean dependent var	−0.083777	S.D. dependent var	0.426532
Sum squared resid	3.886995	S.E. of regression	0.270813
R^2	0.666165	Adjusted R^2	0.596879
$\hat{\rho}$	0.101277	Durbin–Watson	1.790659

Equation 5: Δytm_10yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	−17.2657	6.34052	−2.723	0.0087
d_lr_noncore_1	−0.593376	1.43994	−0.4121	0.6819
$\Delta \mathrm{RPI}_{t-1}$	0.0178583	0.0567205	0.3148	0.7541
d_l_rgdp_1	1.20946	7.07331	0.1710	0.8649
$\Delta \mathrm{LIBOR}_{t-1}$	−0.00196091	0.147223	−0.01332	0.9894
$\Delta \mathrm{ytm}_{t-10}$	−0.145526	0.161009	−0.9038	0.3702
d_lr_LTDebt_CG_1	−4.82816	1.43742	−3.359	0.0015
d_lr_PNFC_MFI_deposits_1	2.18188	1.46647	1.488	0.1427
FTSE_Vol_1	−0.00551641	0.00449640	−1.227	0.2253
EC1	0.665356	0.218995	3.038	0.0037
EC2	−0.0884059	0.0290804	−3.040	0.0037

Mean dependent var	−0.063542	S.D. dependent var	0.293037
Sum squared resid	3.467668	S.E. of regression	0.255788
R^2	0.369026	Adjusted R^2	0.238069
$\hat{\rho}$	0.001812	Durbin–Watson	1.976847

Equation 6: Δlr_LTDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	−0.289252	0.755719	−0.3828	0.7034
d_lr_noncore_1	0.0120274	0.171624	0.07008	0.9444
$\Delta \mathrm{RPI}_{t-1}$	0.00954187	0.00676044	1.411	0.1640
d_l_rgdp_1	−1.60738	0.843059	−1.907	0.0620
$\Delta \mathrm{LIBOR}_{t-1}$	−0.00784951	0.0175473	−0.4473	0.6565
$\Delta \mathrm{ytm}_{t-10}$	0.0106554	0.0191905	0.5552	0.5811
d_lr_LTDebt_CG_1	0.307141	0.171324	1.793	0.0787
d_lr_PNFC_MFI_deposits_1	−0.298457	0.174787	−1.708	0.0936
FTSE_Vol_1	−0.000723212	0.000535921	−1.349	0.1829
EC1	0.0205099	0.0261017	0.7858	0.4355
EC2	−0.00275918	0.00346605	−0.7961	0.4295

Mean dependent var	0.022221	S.D. dependent var	0.034716
Sum squared resid	0.049261	S.E. of regression	0.030487
R^2	0.361353	Adjusted R^2	0.228803
$\hat{\rho}$	−0.053358	Durbin–Watson	2.045446

Equation 7: Δlr_PNFC_MFI_d

	Coefficient	Std. Error	t-ratio	p-value
const	0.0396407	0.516176	0.07680	0.9391
d_lr_noncore_1	0.284382	0.117224	2.426	0.0187
ΔRPI_{t-1}	−0.00800502	0.00461756	−1.734	0.0888
d_l_rgdp_1	1.51661	0.575832	2.634	0.0110
ΔLIBOR_{t-1}	0.0161359	0.0119853	1.346	0.1839
Δytm_{t-10}	−0.00773745	0.0131076	−0.5903	0.5575
d_lr_LTDebt_CG_1	−0.0138027	0.117019	−0.1180	0.9066
d_lr_PNFC_MFI_deposits_1	−0.330726	0.119384	−2.770	0.0077
FTSE_Vol_1	−9.51081e–006	0.000366048	−0.02598	0.9794
EC1	0.00885824	0.0178282	0.4969	0.6213
EC2	−0.00122070	0.00236741	−0.5156	0.6083

Mean dependent var	0.011780	S.D. dependent var	0.022455
Sum squared resid	0.022982	S.E. of regression	0.020823
R^2	0.287827	Adjusted R^2	0.140018
$\hat{\rho}$	0.078751	Durbin–Watson	1.786397

Appendix B

Principal Components Analysis

Principal Components Analysis

B.1 Data Spaces for PCA

B.1.1 Undifferenced, Small:

Variables

Scree Plot

Table B.1: Variables for Undifferenced Small panel

lr_noncore
lr_M4_sec
lr_MMI_liab_total
lr_MMI_asset_total

Figure B.1: Scree plot of Undifferenced Small panel

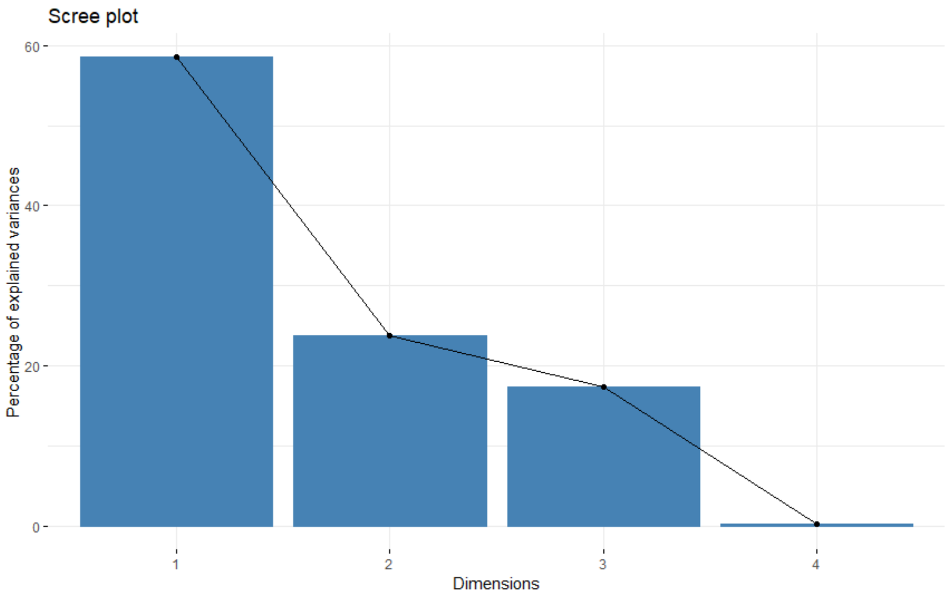
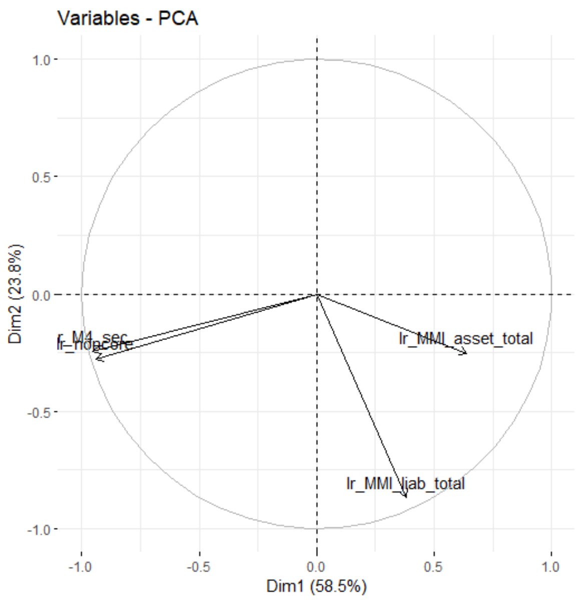


Figure B.2: Biplot of Undifferenced Small panel



Biplot

Table B.2: Principal Components summary for Undifferenced Small panel

	Comp.1	Comp.2	Comp.3	Comp.4
Standard deviation	1.5302416	0.9753368	0.8346909	0.101833102
Proportion of Variance	0.5854098	0.2378204	0.1741772	0.002592495
Cumulative Proportion	0.5854098	0.8232303	0.9974075	1.000000000

Importance of components

Table B.3: Variables for Differenced Small panel

d_lr_noncore
d_lr_M4_sec
d_lr_MMI_liab_total
d_lr_MMI_asset_total

B.1.2 Differenced, Small:

Variables

Scree Plot

Figure B.3: Scree plot of Differenced Small panel

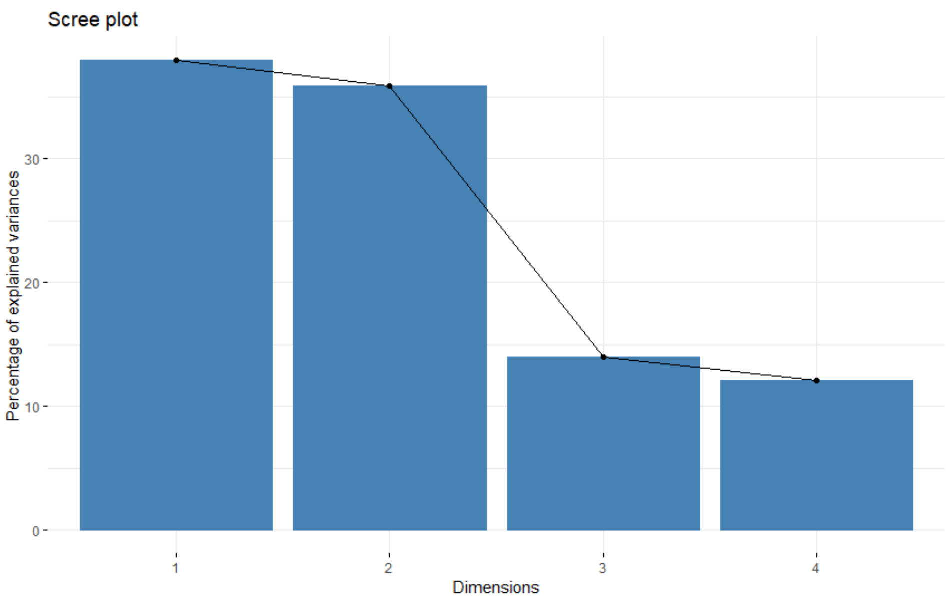
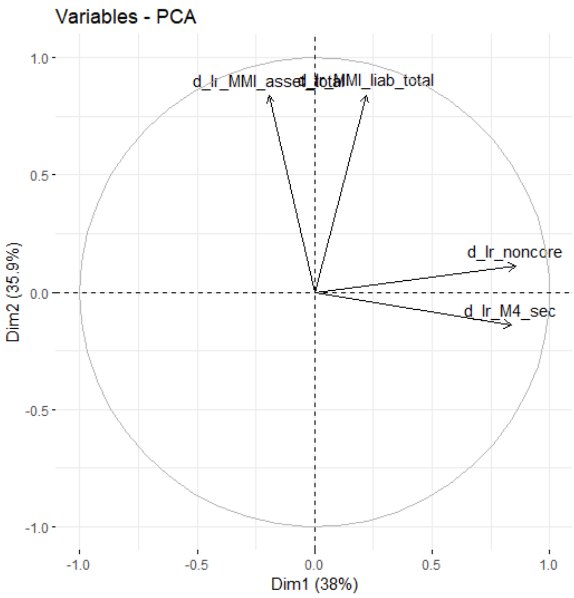


Figure B.4: Biplot of Differenced Small panel



Biplot

Table B.4: Principal Components summary for Differenced Small panel

	Comp.1	Comp.2	Comp.3	Comp.4
Standard deviation	1.232286	1.1988487	0.7484104	0.6957843
Proportion of Variance	0.379632	0.3593095	0.1400295	0.1210289
Cumulative Proportion	0.379632	0.7389415	0.8789711	1.0000000

Importance of components

Table B.5: Variables for Undifferenced Large panel

lr_noncore
lr_M4_sec
lr_MMI_liab_total
lr_MMI_asset_total
lr_MMI_PNFC
lr_MMI_MFI_asset
lr_MMI_OFI_asset
lr_MMI_OFI_liab
lr_MMI_IPF
lr_MMI_CG
lr_MMI_LG
lr_MMI_HH
lr_MMI_RoW

B.1.3 Undifferenced, Large:

Variables

Scree Plot

Figure B.5: Scree plot of Undifferenced Large panel

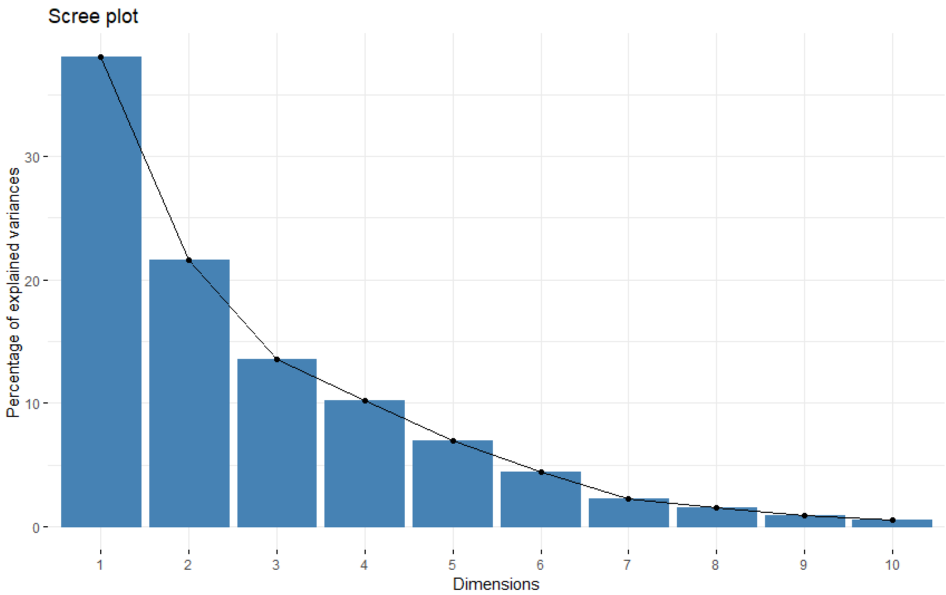
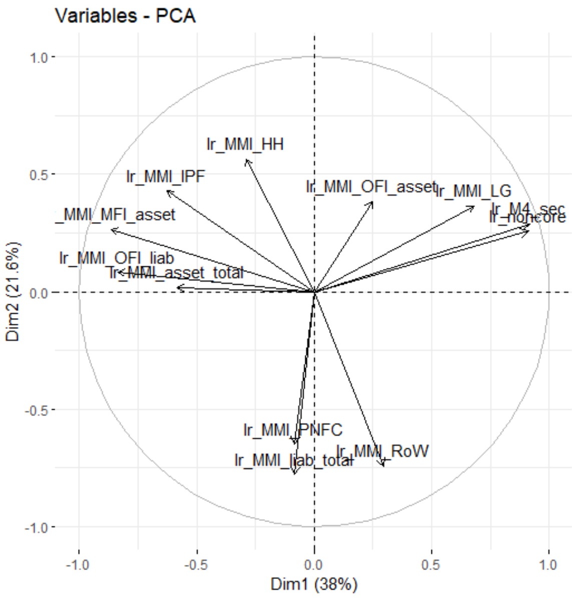


Figure B.6: Biplot of Undifferenced Large panel



Biplot

Table B.6: Augmented Dickey-Fuller tests of components of Undifferenced Large panel

Variable	**ADF p-value**
lr_noncore	0.67
lr_M4_sec	0.41
lr_MMI_liab_total	0.02
lr_MMI_asset_total	0.00
lr_MMI_PNFC	0.07
lr_MMI_MFI_asset	0.74
lr_MMI_OFI_asset	0.04
lr_MMI_OFI_liab	0.01
lr_MMI_IPF	0.07
lr_MMI_CG	0.53
lr_MMI_LG	0.07
lr_MMI_HH	0.04
lr_MMI_RoW	0.00

Importance of components

B.1.4 Differenced, Large:

Variables

Scree Plot

Table B.7: Variables for Differenced Large panel

d_lr_noncore
d_lr_M4_sec
d_lr_MMI_liab_total
d_lr_MMI_asset_total
d_lr_MMI_PNFC
d_lr_MMI_MFI_asset
d_lr_MMI_OFI_asset
d_lr_MMI_OFI_liab
d_lr_MMI_IPF
d_lr_MMI_CG
d_lr_MMI_LG
d_lr_MMI_HH
d_lr_MMI_RoW

Figure B.7: Scree plot of Differenced Large panel

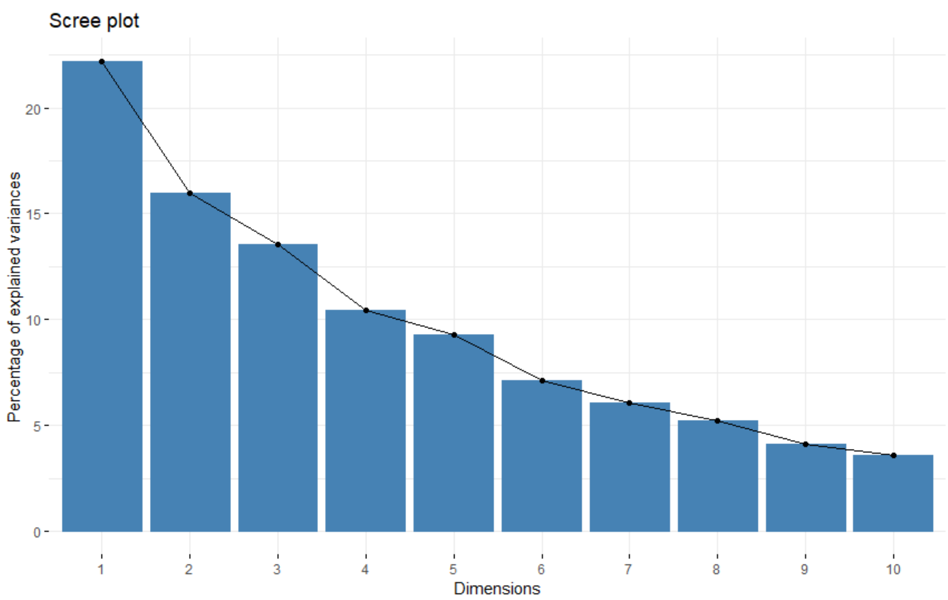


Table B.8: Principal Components summary for Undifferenced Large panel

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12
Standard deviation	2.13584	1.60850	1.27410	1.10510	0.91496	0.73084	0.51557	0.43381	0.32314	0.24819	0.09464	0.07727
Proportion of Variance	0.38015	0.21560	0.13527	0.10177	0.06976	0.04451	0.02215	0.01568	0.00870	0.00513	0.00074	0.00049
Cumulative Proportion	0.38015	0.59576	0.73104	0.83281	0.90257	0.94708	0.96923	0.98492	0.99362	0.99875	0.99950	1.00000

Biplot

Figure B.8: Biplot of Differenced Large panel

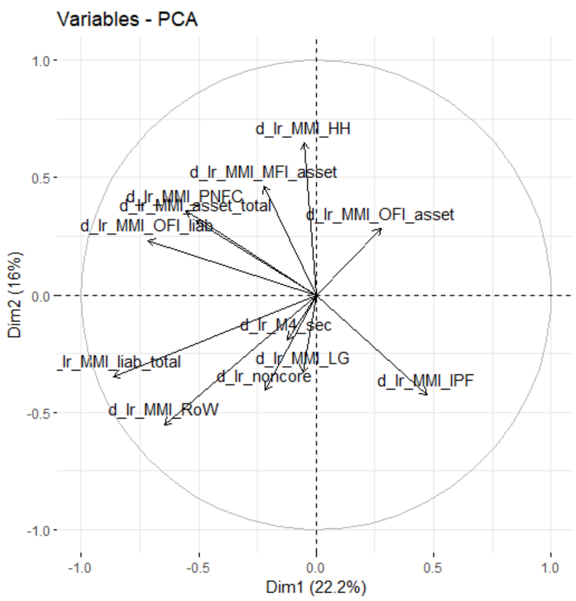
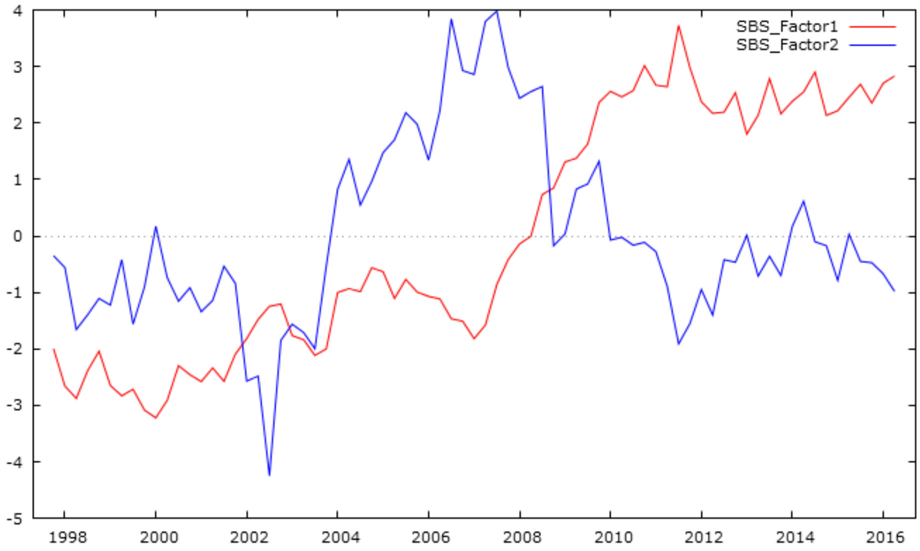


Figure B.9: Time series plot of extracted shadow banking factors



Importance of components

B.2 Time-series plot of Factors

Table B.9: Principal Components summary for Differenced Large panel

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12
Standard deviation	1.63149	1.38494	1.27449	1.11775	1.05363	0.92387	0.85444	0.78938	0.70124	0.65674	0.53873	0.12743
Proportion of Variance	0.22181	0.15983	0.13536	0.10411	0.09251	0.07112	0.06084	0.05192	0.04097	0.03594	0.02418	0.00135
Cumulative Proportion	0.22181	0.38165	0.51701	0.62113	0.71364	0.78477	0.84561	0.89753	0.93851	0.97446	0.99864	1.00000

Table B.10: Information criteria for lag selection, group C1 models

lags	loglik	p(LR)	AIC	BIC	HQC
1	741.11706		-22.037235	-19.244776*	-20.944951
2	816.73764	0.00000	-22.424588	-17.398161	-20.458476
3	875.90524	0.00004	-22.263508	-15.003114	-19.423569
4	967.64416	0.00000	-23.188139	-13.693777	-19.474372
5	1073.91728	0.00000	-24.597243	-12.868913	-20.009648
6	1330.60625	0.00000	-31.020208*	-17.057911	-25.558786*

B.3 Factor Models

B.3.1 C1, Factor-Augmented Vector Error Correction Models

VAR lag selection for group C1

Table B.11: Trace and maximum eigenvalue tests for group C1

Rank	Eigenvalue	Trace test [p-value]	Lmax test [p-value]
0	0.61821	187.03 [0.0005]	61.625 [0.0025]
1	0.51867	125.41 [0.0501]	46.796 [0.0391]
2	0.43820	78.610 [0.4143]	36.902 [0.1087]
3	0.22311	41.708 [0.9135]	16.157 [0.9393]
4	0.17210	25.551 [0.8995]	12.087 [0.9184]
5	0.15299	13.463 [0.8681]	10.627 [0.6907]
6	0.040131	2.8365 [0.9665]	2.6213 [0.9587]
7	0.0033557	0.21513 [0.6428]	0.21513 [0.6428]

Johansen rank selection for group C1

C1a, Factor-Augmented VECM system with two shadow banking system activity factors, log GDP deflator, log real GDP, 1-month LIBOR, 20-year gilt yield, log real deposits held by UK Private Non-Financial Corporates (lr_PNFC_deposits), log real long-term debt outstanding as a liability of central government, and FTSE volatility in short-run equations

VECM system, lag order 2
Maximum likelihood estimates, observations 2000:3–2016:2 ($T = 64$)
Cointegration rank = 1
Case 3: Unrestricted constant

Restrictions on beta: b1 = -1

Cointegrating vectors (standard errors in parentheses)

SBS_Factor1_{t-1}	-1.00000
	(0.00000)
SBS_Factor2_{t-1}	1.21453
	(0.457903)
l_gdpdef_{t-1}	125.577
	(40.7837)
l_rgdp_{t-1}	-119.636
	(34.2762)
LIBOR_1m_{t-1}	-2.34571
	(0.488553)
$\text{ytm\_20yrGilt}_{t-1}$	-5.84087
	(1.36978)
$\text{lr\_PNFC\_deposits}_{t-1}$	20.5778
	(12.1653)
$\text{lr\_LTDebt\_CG}_{t-1}$	-28.2994
	(5.98395)

Adjustment vectors (standard errors in parentheses)

SBS_Factor1$_{t-1}$	0.0173887
	(0.0234098)
SBS_Factor2$_{t-1}$	0.0141519
	(0.0474180)
l_gdpdef$_{t-1}$	0.000234749
	(0.000265375)
l_rgdp$_{t-1}$	0.000616720
	(0.000252376)
LIBOR_1m$_{t-1}$	0.0429598
	(0.0146164)
ytm_20yrGilt$_{t-1}$	0.0480830
	(0.00959577)
lr_PNFC_deposits$_{t-1}$	0.00141455
	(0.00114784)
lr_LTDebt_CG$_{t-1}$	0.000741032
	(0.00161967)

Log-likelihood = 785.726

Determinant of covariance matrix = 0.00000

AIC = -20.0539

BIC = -15.1964

HQC = -18.1403

Equation 1: ΔSBS_Factor1

	Coefficient	Std. Error	t-ratio	p-value
const	19.1907	25.7995	0.7438	0.4603
d_SBS_Factor1_1	−0.0629097	0.137212	−0.4585	0.6485
d_SBS_Factor2_1	−0.0399412	0.0758163	−0.5268	0.6005
d_l_gdpdef_1	−14.1922	12.7572	−1.112	0.2709
d_l_rgdp_1	−2.82896	11.7347	−0.2411	0.8104
ΔLIBOR$_{t-1}$	0.143102	0.195340	0.7326	0.4670
Δytm$_{t-20}$	0.240002	0.280023	0.8571	0.3953
d_lr_PNFC_deposits_1	1.07614	2.56222	0.4200	0.6762
d_lr_LTDebt_CG_1	0.190477	2.06105	0.09242	0.9267
FTSE_Vol_1	0.00693117	0.00772870	0.8968	0.3739
EC1	0.0173887	0.0234098	0.7428	0.4609

Mean dependent var	0.089722	S.D. dependent var	0.402435
Sum squared resid	9.523594	S.E. of regression	0.423899
R^2	0.066600	Adjusted R^2	-0.109514
$\hat{\rho}$	−0.059563	Durbin–Watson	2.091345

Equation 2: ΔSBS_Factor2

	Coefficient	Std. Error	t-ratio	p-value
const	15.1775	52.2585	0.2904	0.7726
d_SBS_Factor1_1	−0.250320	0.277932	−0.9007	0.3718
d_SBS_Factor2_1	−0.127386	0.153571	−0.8295	0.4105
d_l_gdpdef_1	14.2779	25.8405	0.5525	0.5829
d_l_rgdp_1	27.8160	23.7694	1.170	0.2471
ΔLIBOR$_{t-1}$	−0.220656	0.395674	−0.5577	0.5794
Δytm$_{t-20}$	−0.0665184	0.567204	−0.1173	0.9071
d_lr_PNFC_deposits_1	4.71506	5.18992	0.9085	0.3677
d_lr_LTDebt_CG_1	0.432416	4.17477	0.1036	0.9179
FTSE_Vol_1	0.00755645	0.0156549	0.4827	0.6313
EC1	0.0141519	0.0474180	0.2985	0.7665

Mean dependent var	−0.003823	S.D. dependent var	0.828717
Sum squared resid	39.07428	S.E. of regression	0.858633
R^2	0.096895	Adjusted R^2	-0.073502
$\hat{\rho}$	−0.127495	Durbin–Watson	2.237635

Equation 3: Δl_gdpdef

	Coefficient	Std. Error	t-ratio	p-value
const	0.264708	0.292465	0.9051	0.3695
d_SBS_Factor1_1	0.00261089	0.00155545	1.679	0.0991
d_SBS_Factor2_1	0.000195126	0.000859459	0.2270	0.8213
d_l_gdpdef_1	−0.229493	0.144616	−1.587	0.1185
d_l_rgdp_1	−0.112579	0.133026	−0.8463	0.4012
ΔLIBOR$_{t-1}$	0.00379396	0.00221439	1.713	0.0925
Δytm$_{t-20}$	−0.00351940	0.00317436	−1.109	0.2726
d_lr_PNFC_deposits_1	0.0291612	0.0290454	1.004	0.3199
d_lr_LTDebt_CG_1	−0.0285282	0.0233642	−1.221	0.2275
FTSE_Vol_1	2.15901e–005	8.76130e–005	0.2464	0.8063
EC1	0.000234749	0.000265375	0.8846	0.3804

Mean dependent var	0.004801	S.D. dependent var	0.004818
Sum squared resid	0.001224	S.E. of regression	0.004805
R^2	0.163068	Adjusted R^2	0.005157
$\hat{\rho}$	0.009062	Durbin–Watson	1.972657

Equation 4: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.681665	0.278139	2.451	0.0176
d_SBS_Factor1_1	0.000144244	0.00147926	0.09751	0.9227
d_SBS_Factor2_1	−0.00108571	0.000817360	−1.328	0.1898
d_l_gdpdef_1	−0.237944	0.137533	−1.730	0.0894
d_l_rgdp_1	0.696582	0.126510	5.506	0.0000
ΔLIBOR$_{t-1}$	0.00106489	0.00210592	0.5057	0.6152
Δytm$_{t-20}$	−0.00134955	0.00301887	−0.4470	0.6567
d_lr_PNFC_deposits_1	0.0236879	0.0276227	0.8576	0.3950
d_lr_LTDebt_CG_1	−0.0183880	0.0222197	−0.8276	0.4116
FTSE_Vol_1	6.61444e–006	8.33215e–005	0.07938	0.9370
EC1	0.000616720	0.000252376	2.444	0.0179

Mean dependent var	0.004298	S.D. dependent var	0.006389
Sum squared resid	0.001107	S.E. of regression	0.004570
R^2	0.569538	Adjusted R^2	0.488319
$\hat{\rho}$	−0.086181	Durbin–Watson	2.144622

Equation 5: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	47.5116	16.1084	2.949	0.0047
d_SBS_Factor1_1	0.0993907	0.0856711	1.160	0.2512
d_SBS_Factor2_1	0.0272250	0.0473373	0.5751	0.5676
d_l_gdpdef_1	−3.33627	7.96519	−0.4189	0.6770
d_l_rgdp_1	19.6299	7.32679	2.679	0.0098
ΔLIBOR$_{t-1}$	0.267879	0.121964	2.196	0.0325
Δytm$_{t-20}$	−0.115613	0.174838	−0.6613	0.5113
d_lr_PNFC_deposits_1	1.01487	1.59977	0.6344	0.5286
d_lr_LTDebt_CG_1	−1.62843	1.28685	−1.265	0.2112
FTSE_Vol_1	−0.0157766	0.00482555	−3.269	0.0019
EC1	0.0429598	0.0146164	2.939	0.0049

Mean dependent var	−0.086511	S.D. dependent var	0.429329
Sum squared resid	3.712641	S.E. of regression	0.264669
R^2	0.680286	Adjusted R^2	0.619963
$\hat{\rho}$	0.098141	Durbin–Watson	1.790741

Equation 6: Δytm_20yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	53.0183	10.5753	5.013	0.0000
d_SBS_Factor1_1	0.0544695	0.0562438	0.9685	0.3372
d_SBS_Factor2_1	−0.0785162	0.0310774	−2.526	0.0145
d_l_gdpdef_1	−4.50594	5.22922	−0.8617	0.3927
d_l_rgdp_1	−1.42035	4.81010	−0.2953	0.7689
ΔLIBOR$_{t-1}$	0.0915086	0.0800707	1.143	0.2582
Δytm$_{t-20}$	−0.227493	0.114783	−1.982	0.0527
d_lr_PNFC_deposits_1	0.115052	1.05026	0.1095	0.9132
d_lr_LTDebt_CG_1	−4.96596	0.844830	−5.878	0.0000
FTSE_Vol_1	0.00121250	0.00316802	0.3827	0.7034
EC1	0.0480830	0.00959577	5.011	0.0000

Mean dependent var	−0.039531	S.D. dependent var	0.231049
Sum squared resid	1.600162	S.E. of regression	0.173758
R^2	0.524211	Adjusted R^2	0.434439
$\hat{\rho}$	−0.001229	Durbin–Watson	1.980461

Equation 7: Δlr_PNFC_depos

	Coefficient	Std. Error	t-ratio	p-value
const	1.56937	1.26502	1.241	0.2202
d_SBS_Factor1_1	−0.00340503	0.00672788	−0.5061	0.6149
d_SBS_Factor2_1	−0.00177348	0.00371747	−0.4771	0.6353
d_l_gdpdef_1	−0.715632	0.625518	−1.144	0.2577
d_l_rgdp_1	1.26691	0.575383	2.202	0.0320
ΔLIBOR$_{t-1}$	0.00343574	0.00957804	0.3587	0.7212
Δytm$_{t-20}$	0.00302072	0.0137303	0.2200	0.8267
d_lr_PNFC_deposits_1	−0.325128	0.125632	−2.588	0.0124
d_lr_LTDebt_CG_1	0.0860259	0.101058	0.8512	0.3985
FTSE_Vol_1	6.07151e–006	0.000378958	0.01602	0.9873
EC1	0.00141455	0.00114784	1.232	0.2233

Mean dependent var	0.010924	S.D. dependent var	0.021537
Sum squared resid	0.022897	S.E. of regression	0.020785
R^2	0.216434	Adjusted R^2	0.068591
$\hat{\rho}$	0.034652	Durbin–Watson	1.860952

Equation 8: Δlr_LTDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	0.844675	1.78501	0.4732	0.6380
d_SBS_Factor1_1	0.0173813	0.00949341	1.831	0.0727
d_SBS_Factor2_1	0.00404649	0.00524555	0.7714	0.4439
d_l_gdpdef_1	1.40368	0.882640	1.590	0.1177
d_l_rgdp_1	−1.03705	0.811898	−1.277	0.2071
ΔLIBOR$_{t-1}$	−0.00994300	0.0135151	−0.7357	0.4652
Δytm$_{t-20}$	0.0277259	0.0193742	1.431	0.1583
d_lr_PNFC_deposits_1	−0.238833	0.177274	−1.347	0.1836
d_lr_LTDebt_CG_1	0.528778	0.142599	3.708	0.0005
FTSE_Vol_1	−0.000898642	0.000534730	−1.681	0.0987
EC1	0.000741032	0.00161967	0.4575	0.6492

Mean dependent var	0.022390	S.D. dependent var	0.034964
Sum squared resid	0.045589	S.E. of regression	0.029329
R^2	0.408049	Adjusted R^2	0.296360
$\hat{\rho}$	−0.011821	Durbin–Watson	1.969369

C1b,

VECM system, lag order 2

Maximum likelihood estimates, observations 2000:3–2016:2 ($T = 64$)

Cointegration rank = 2

Case 3: Unrestricted constant

Restrictions on beta: b[1,1] = -1 b[1,2] = 0 b[2,1] = 0 b[2,2] = -1

Cointegrating vectors (standard errors in parentheses)

SBS_Factor1$_{t-1}$	−1.00000	0.00000
	(0.00000)	(0.00000)
SBS_Factor2$_{t-1}$	0.00000	−1.00000
	(0.00000)	(0.00000)
l_gdpdef$_{t-1}$	−96.0138	−182.450
	(23.8398)	(45.7867)
l_rgdp$_{t-1}$	85.4001	168.819
	(20.9785)	(40.2912)
LIBOR_1m$_{t-1}$	0.527211	2.36546
	(0.225245)	(0.432605)
ytm_20yrGilt$_{t-1}$	4.14853	8.22490
	(0.935158)	(1.79606)
lr_PNFC_deposits$_{t-1}$	−20.9717	−34.2103
	(7.45139)	(14.3111)
lr_LTDebt_CG$_{t-1}$	25.0861	43.9557
	(3.51255)	(6.74618)

Adjustment vectors (standard errors in parentheses)

SBS_Factor1$_{t-1}$	0.216317	−0.104260
	(0.102169)	(0.0501020)
SBS_Factor2$_{t-1}$	−0.159179	0.0552550
	(0.213450)	(0.104672)
l_gdpdef$_{t-1}$	−0.000928238	0.000200954
	(0.00119101)	(0.000584052)
l_rgdp$_{t-1}$	0.000997914	−0.000908343
	(0.00114246)	(0.000560242)
LIBOR_1m$_{t-1}$	−0.0647954	−0.00714021
	(0.0644060)	(0.0315836)
ytm_20yrGilt$_{t-1}$	0.0730613	−0.0688378
	(0.0433397)	(0.0212530)
lr_PNFC_deposits$_{t-1}$	0.0159102	−0.00777638
	(0.00476672)	(0.00233751)
lr_LTDebt_CG$_{t-1}$	−0.0217623	0.00850515
	(0.00658957)	(0.00323141)

Log-likelihood = 809.124

Determinant of covariance matrix = 0.00000

AIC = −20.7851

BIC = −15.9276

HQC = −18.8715

Equation 1: ΔSBS_Factor1

	Coefficient	Std. Error	t-ratio	p-value
const	−2.98563	27.6524	−0.1080	0.9144
d_SBS_Factor1_1	0.0175607	0.140594	0.1249	0.9011
d_SBS_Factor2_1	−0.0723002	0.0761711	−0.9492	0.3470
d_l_gdpdef_1	−9.68669	12.7252	−0.7612	0.4500
d_l_rgdp_1	−8.59420	11.8759	−0.7237	0.4726
ΔLIBOR$_{t-1}$	0.130688	0.191869	0.6811	0.4989
Δytm$_{t-20}$	0.180573	0.276506	0.6531	0.5167
d_lr_PNFC_deposits_1	−0.192738	2.59427	−0.07429	0.9411
d_lr_LTDebt_CG_1	1.09478	2.07335	0.5280	0.5998
FTSE_Vol_1	0.00939051	0.00768652	1.222	0.2274
EC1	0.216317	0.102169	2.117	0.0391
EC2	−0.104260	0.0501020	−2.081	0.0425

Mean dependent var	0.089722	S.D. dependent var	0.402435
Sum squared resid	8.832088	S.E. of regression	0.416147
R^2	0.134374	Adjusted R^2	-0.069303
$\hat{\rho}$	−0.036888	Durbin–Watson	2.068671

Equation 2: ΔSBS_Factor2

	Coefficient	Std. Error	t-ratio	p-value
const	34.5002	57.7709	0.5972	0.5530
d_SBS_Factor1_1	−0.320436	0.293726	−1.091	0.2804
d_SBS_Factor2_1	−0.0991912	0.159135	−0.6233	0.5359
d_l_gdpdef_1	10.3521	26.5853	0.3894	0.6986
d_l_rgdp_1	32.8394	24.8109	1.324	0.1915
ΔLIBOR$_{t-1}$	−0.209840	0.400849	−0.5235	0.6029
Δytm$_{t-20}$	−0.0147364	0.577673	−0.02551	0.9797
d_lr_PNFC_deposits_1	5.82066	5.41991	1.074	0.2879
d_lr_LTDebt_CG_1	−0.355524	4.33160	−0.08208	0.9349
FTSE_Vol_1	0.00541357	0.0160586	0.3371	0.7374
EC1	−0.159179	0.213450	−0.7457	0.4592
EC2	0.0552550	0.104672	0.5279	0.5999

Mean dependent var	−0.003823	S.D. dependent var	0.828717
Sum squared resid	38.54929	S.E. of regression	0.869407
R^2	0.109029	Adjusted R^2	-0.100611
$\hat{\rho}$	−0.130457	Durbin–Watson	2.252751

Equation 3: Δl_gdpdef

	Coefficient	Std. Error	t-ratio	p-value
const	0.394356	0.322351	1.223	0.2268
d_SBS_Factor1_1	0.00214044	0.00163894	1.306	0.1974
d_SBS_Factor2_1	0.000384305	0.000887946	0.4328	0.6670
d_l_gdpdef_1	−0.255833	0.148341	−1.725	0.0907
d_l_rgdp_1	−0.0788741	0.138440	−0.5697	0.5714
ΔLIBOR_{t-1}	0.00386653	0.00223666	1.729	0.0899
Δytm_{t-20}	−0.00317196	0.00322331	−0.9841	0.3297
d_lr_PNFC_deposits_1	0.0365794	0.0302421	1.210	0.2320
d_lr_LTDebt_CG_1	−0.0338150	0.0241695	−1.399	0.1678
FTSE_Vol_1	7.21216e–006	8.96038e–005	0.08049	0.9362
EC1	−0.000928238	0.00119101	−0.7794	0.4394
EC2	0.000200954	0.000584052	0.3441	0.7322

Mean dependent var	0.004801	S.D. dependent var	0.004818
Sum squared resid	0.001200	S.E. of regression	0.004851
R^2	0.179231	Adjusted R^2	-0.013891
$\hat{\rho}$	−0.002472	Durbin–Watson	1.995883

Equation 4: Δl_rgdp

	Coefficient	Std. Error	t-ratio	p-value
const	0.639170	0.309210	2.067	0.0438
d_SBS_Factor1_1	0.000298444	0.00157212	0.1898	0.8502
d_SBS_Factor2_1	−0.00114771	0.000851747	−1.347	0.1838
d_l_gdpdef_1	−0.229311	0.142294	−1.612	0.1132
d_l_rgdp_1	0.685535	0.132797	5.162	0.0000
ΔLIBOR$_{t-1}$	0.00104110	0.00214548	0.4853	0.6296
Δytm$_{t-20}$	−0.00146343	0.00309190	−0.4733	0.6380
d_lr_PNFC_deposits_1	0.0212564	0.0290092	0.7327	0.4671
d_lr_LTDebt_CG_1	−0.0166551	0.0231842	−0.7184	0.4758
FTSE_Vol_1	1.13271e–005	8.59510e–005	0.1318	0.8957
EC1	0.000997914	0.00114246	0.8735	0.3865
EC2	−0.000908343	0.000560242	−1.621	0.1111

Mean dependent var	0.004298	S.D. dependent var	0.006389
Sum squared resid	0.001104	S.E. of regression	0.004653
R^2	0.570526	Adjusted R^2	0.469473
$\hat{\rho}$	−0.084775	Durbin–Watson	2.138022

Equation 5: ΔLIBOR_1m

	Coefficient	Std. Error	t-ratio	p-value
const	59.5240	17.4317	3.415	0.0013
d_SBS_Factor1_1	0.0558018	0.0886282	0.6296	0.5318
d_SBS_Factor2_1	0.0447532	0.0480171	0.9320	0.3557
d_l_gdpdef_1	−5.77681	8.02180	−0.7201	0.4747
d_l_rgdp_1	22.7528	7.48639	3.039	0.0037
ΔLIBOR$_{t-1}$	0.274604	0.120951	2.270	0.0274
Δytm$_{t-20}$	−0.0834218	0.174306	−0.4786	0.6343
d_lr_PNFC_deposits_1	1.70220	1.63539	1.041	0.3029
d_lr_LTDebt_CG_1	−2.11827	1.30701	−1.621	0.1112
FTSE_Vol_1	−0.0171087	0.00484547	−3.531	0.0009
EC1	−0.0647954	0.0644060	−1.006	0.3191
EC2	−0.00714021	0.0315836	−0.2261	0.8220

Mean dependent var	−0.086511	S.D. dependent var	0.429329
Sum squared resid	3.509743	S.E. of regression	0.262333
R^2	0.697759	Adjusted R^2	0.626643
$\hat{\rho}$	0.027278	Durbin–Watson	1.907327

Equation 6: Δytm_20yrGilt

	Coefficient	Std. Error	t-ratio	p-value
const	50.2338	11.7300	4.283	0.0001
d_SBS_Factor1_1	0.0645736	0.0596392	1.083	0.2840
d_SBS_Factor2_1	−0.0825793	0.0323114	−2.556	0.0136
d_l_gdpdef_1	−3.94020	5.39798	−0.7299	0.4688
d_l_rgdp_1	−2.14426	5.03770	−0.4256	0.6722
ΔLIBOR$_{t-1}$	0.0899499	0.0813897	1.105	0.2743
Δytm$_{t-20}$	−0.234955	0.117293	−2.003	0.0505
d_lr_PNFC_deposits_1	−0.0442743	1.10048	−0.04023	0.9681
d_lr_LTDebt_CG_1	−4.85242	0.879503	−5.517	0.0000
FTSE_Vol_1	0.00152131	0.00326059	0.4666	0.6428
EC1	0.0730613	0.0433397	1.686	0.0979
EC2	−0.0688378	0.0212530	−3.239	0.0021

Mean dependent var	−0.039531	S.D. dependent var	0.231049
Sum squared resid	1.589259	S.E. of regression	0.176527
R^2	0.527452	Adjusted R^2	0.416265
$\hat{\rho}$	0.007455	Durbin–Watson	1.971133

Equation 7: Δlr_PNFC_depos

	Coefficient	Std. Error	t-ratio	p-value
const	−0.0465887	1.29013	−0.03611	0.9713
d_SBS_Factor1_1	0.00245872	0.00655942	0.3748	0.7093
d_SBS_Factor2_1	−0.00413144	0.00355377	−1.163	0.2504
d_l_gdpdef_1	−0.387322	0.593697	−0.6524	0.5171
d_l_rgdp_1	0.846808	0.554071	1.528	0.1326
ΔLIBOR_{t-1}	0.00253117	0.00895165	0.2828	0.7785
Δytm_{t-20}	−0.00130979	0.0129004	−0.1015	0.9195
d_lr_PNFC_deposits_1	−0.417590	0.121036	−3.450	0.0011
d_lr_LTDebt_CG_1	0.151921	0.0967321	1.571	0.1225
FTSE_Vol_1	0.000185280	0.000358616	0.5167	0.6076
EC1	0.0159102	0.00476672	3.338	0.0016
EC2	−0.00777638	0.00233751	−3.327	0.0016

Mean dependent var	0.010924	S.D. dependent var	0.021537
Sum squared resid	0.019225	S.E. of regression	0.019415
R^2	0.342089	Adjusted R^2	0.187287
$\hat{\rho}$	0.003884	Durbin–Watson	1.976835

Equation 8: Δlr_LTDebt_CG

	Coefficient	Std. Error	t-ratio	p-value
const	3.35332	1.78348	1.880	0.0658
d_SBS_Factor1_1	0.00827825	0.00906782	0.9129	0.3656
d_SBS_Factor2_1	0.00770703	0.00491277	1.569	0.1229
d_l_gdpdef_1	0.894000	0.820734	1.089	0.2812
d_l_rgdp_1	−0.384870	0.765955	−0.5025	0.6175
ΔLIBOR_{t-1}	−0.00853873	0.0123749	−0.6900	0.4933
Δytm_{t-20}	0.0344487	0.0178337	1.932	0.0590
d_lr_PNFC_deposits_1	−0.0952932	0.167322	−0.5695	0.5715
d_lr_LTDebt_CG_1	0.426481	0.133724	3.189	0.0024
FTSE_Vol_1	−0.00117685	0.000495754	−2.374	0.0214
EC1	−0.0217623	0.00658957	−3.303	0.0018
EC2	0.00850515	0.00323141	2.632	0.0112

Mean dependent var	0.022390	S.D. dependent var	0.034964
Sum squared resid	0.036740	S.E. of regression	0.026840
R^2	0.522950	Adjusted R^2	0.410702
$\hat{\rho}$	-0.049775	Durbin–Watson	1.995296

Appendix C

Online Technical Appendix

See online technical appendix at:

https://s3.eu-west-2.amazonaws.com/domsilman-thesis-technical-appendix/BSAMatrix.xlsx